Replication Report

"The Relative Efficiency of Skilled Labor across Countries: Measurement and Interpretation", Rossi (2022)

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1 Introduction

Understanding the reasons behind cross-country productivity differences is a central topic in macroeconomics. Originally, richer countries were believed to have a higher factor neutral productivity shifter[1], while differential input quantity and productivity were considered second order (Hall and Jones, 1999). However, this view has been challenged in more recent literature arguing that productivity differences stem from variations in relative efficiency of high- and low-skilled workers across countries (Caselli and Coleman, 2006; Caselli, 2016; Malmberg, 2018). Indeed, while low-skilled workers do not exhibit a significant relative productivity boost in rich countries, high-skilled workers do. There are two opposing views in the literature explaining this phenomenon. On the one hand, Caselli and Coleman (2006) present the "relative technology" interpretation, whereby the productive environment in richer countries more strongly complements high-skill workers. For example, this can be due to firms in richer countries adopting more skill intensive technologies. On the other hand, Jones (2014) presents the "relative human capital" interpretation, whereby the gap between low- and high-skilled workers' human capital is larger in richer countries due to differences in educational quality, training or workers' intrinsic characteristics. Distinguishing between the more dominant interpretation is crucial for development economics and policy making in developing countries: the former suggests that poor countries should invest into skill-biased technology adoption, while the latter implies that investing in education should be the priority.

Rossi (2022) bridges the gap between these interpretations. In short, he leverages rich cross-country micro-data to provide a novel computation of relative skill efficiency, as opposed to the more traditional use of Mincerian return imputations. With this, Rossi confirms that relative skill

[1] If you take the example of a standard Cobb-Douglas production function ($Y = AK^{\alpha}L^{1-\alpha}$) this would be represented by a higher A for the richer country.

efficiency does increase with GDP. Then, by introducing a simple CES production function setting, he separates human capital from technology effects and finds that skill-biased technologies explain most productivity gaps (approximately 83 to 95%), while human capital differences explain a much smaller percentage (the remaining 5 to 18%). Following from this, Rossi uses the migrant aspect of his data to support the technology explanation. He finds that high-skilled migrants from poor countries earn similar skill premiums to native workers in rich countries, meaning education quality differences are not the main factor behind global productivity gaps. Lastly, to robustly verify this finding, Rossi uses development accounting to show limited gains from closing education gaps. Even if a poor country had the same relative human capital as a rich country, its GDP per worker would still be far below rich-country levels.

This report replicates the findings of Rossi (2022). More specifically, it draws on the author's openly accessible STATA replication package to exactly replicate, in R, Tables 2, 3, and 4, as well as Figures 2 and 8 from the paper[2]. In section 2, I present the author's methodology and use these five exhibits to discuss the paper's findings in more detail. In section 3, I conclude.

2 The Paper

2.1 Measuring Relative Skill Efficiency

To compute relative skill efficiency, one first needs to build comparable estimates of the two required inputs: the skill premium and the relative supply of skilled labor. Traditionally, the literature relied on the Mincerian returns to schooling approach[3] to compute the former, while the latter has predominantly been measured using education levels. However, this approach provides a downward biased estimate of the relative efficiency of workers across countries: Mincerian returns are not comparable across countries, thus underestimating variability in skill premia as well as providing inaccurate wage estimates, and assuming education levels translate directly to workforce composition does not account for employment rates or hours worked. In Rossi (2022), the author uses available wage data, while also assuming a CES production function which accounts for a convex wage returns to schooling, to compute a more accurate measure of the skill premia. The micro-data also provides information on employment rates and hours worked which allow for a direct measure of skill supply at both the intensive and extensive margins. Both these factors serve as far more accurate inputs when estimating the cross-country relative efficiency of high- and low-skilled workers.

[2] To directly access the author's replication package, use this link. To access my GitHub repository with the R replication code, follow this link.

[3] These assume a log-linear relationship between wages and years of schooling, typically implying a 10% return per additional year.

Rossi (2022) uses these more accurate inputs in a CES production function, in order to solve for relative skill efficiency. The CES production function allows for imperfect substitutability between high- and low-skilled workers. The production function reads,

$$Y_c = A_c F\left[A_{K,c}K_c, G\left(A_{L,c}L_c, A_{H,c}H_c\right)\right] \tag{1}$$

such that,

$$G\left(A_{L,c}L_c, A_{H,c}H_c\right) = \left[\left(A_{H,c}H_c\right)^{\frac{\sigma-1}{\sigma}} + \left(A_{L,c}L_c\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where $_c$ indexes the country, $_H$ and $_L$ index high- and low-skilled workers while H and L denote high- and low-skill labor services, σ is the elasticity of substitution between the two, and A is a factor-biased technology term. Moreover, under perfectly competitive labor markets, the wage ratio reads,

$$\frac{w_{H,c}}{w_{L,c}} = \frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}} \frac{F_H\left(A_{K,c}K_c, A_{H,c}H_c\right)}{F_L\left(A_{K,c}K_c, A_{L,c}L_c\right)}, \tag{3}$$

where w is the wage and Q is the worker's human capital. By taking FOCs for equation (2) and defining high- and low-skill labor services as,

$$H_c = Q_{H,c}\tilde{H}_c \qquad \text{and} \qquad L_c = Q_{L,c}\tilde{L}_c \tag{4}$$

where $\tilde{H}_c$ and $\tilde{L}_c$ are the number of hours worked by each type of worker in country $_c$, Rossi derives a worker's skill premium as,

$$\frac{w_{H,c}}{w_{L,c}} = \left(\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{\tilde{H}_c}{\tilde{L}_c}\right)^{-\frac{1}{\sigma}} \tag{5}$$

where $\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}$ inside the first RHS term is the relative skill efficiency. Notice how it can be split into $\frac{A_{H,c}}{A_{L,c}}$ and $\frac{Q_{H,c}}{Q_{L,c}}$, the skill bias of technology and human capital of skilled labor, respectively. The author proceeds to summarize the cross-country variation of any quantity of interest X_c with the corresponding elasticity with respect to GDP per worker $\theta_X = \frac{\partial \log X_c}{\partial \log y_c}$. Equation (5) becomes,

$$\theta_{AQ} = \theta_A + \theta_Q = \frac{\sigma}{\sigma-1}\theta_W + \frac{1}{\sigma-1}\theta_{\tilde{H}/\tilde{L}} \tag{6}$$

To implement this framework, Rossi calibrates the elasticity of substitution between high- and low-skilled workers to $\sigma = 1.5$[4], defines high-skill workers as having had some tertiary education,

[4] For this, Rossi follows from Ciccone and Peri (2005) who provide a credibly identified estimate from US data.

and low-skill workers as having at most upper secondary degrees. Thus, equation (4) extends to,

$$\tilde{H}_c = \sum_{n \in \mathcal{H}} \frac{w_{H,c,n}}{w_{H,c,\text{ tertiary}}} \tilde{H}_{c,n} \qquad \text{and} \qquad \tilde{L}_c = \sum_{m \in \mathcal{L}} \frac{w_{L,c,m}}{w_{L,c,\text{ upper secondary}}} \tilde{L}_{c,m} \tag{7}$$

where $w_{H,c,n}$, $w_{L,c,m}$, $H_{c,n}$, and $\tilde{L}_{c,m}$ denote wages and total hours worked by high- and low-skill workers with education levels n and m such that $n \in \mathcal{H} = \{\text{some tertiary, tertiary}\}$ and $m \in \mathcal{L} = \{\text{primary or less, lower secondary, upper secondary}\}$. Now, with the analytical framework properly setup, I can move to the results, how they were computed, and their interpretation.

The main equation used to compute the relative skill-efficiency is equation (5). The author runs a log wage regression with the five educational categories as controls on a sample of wage-employed workers with a relatively high degree of labor market attachment. He does this for 12 different countries for which detailed microdata on individual wages, employment, and hours worked are available. $w_{H,c,n}$ and $w_{L,c,m}$, the LHS components of equation (5), are computed as the exponentials of those estimates. Then, the author computes $\tilde{H}_{c,n}$ and $\tilde{L}_{c,m}$ by summing the hours worked by all workers in the relevant education category. With $\frac{w_{H,c,n}}{w_{L,c,m}}$ and $\frac{w_{H,c}}{w_{L,c}}$ estimated, the relative skill efficiency $\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}$ can be backed out. To facilitate cross-country analysis, US values of relative skill efficiency are normalized to one.

The country specific levels of skill premium, relative skill supply, and efficiency are reported in the original paper's Table 1. The results establish multiple core results. Firstly, educational attainment data suggests a relative supply of skilled labor which is less positively correlated with GDP than what the author finds. This implies larger cross-country gaps in relative skill efficiency for a given skill premium. Secondly, estimates using Mincerian returns are less negatively correlated with GDP than what the author finds, thus implying smaller cross-country gaps in relative skill efficiency. The latter result dominates the former. Hence, even if the the micro-data estimates of gaps in relative skill efficiency are large, they are slightly smaller to the ones made with the traditional sources. However, Table 1 raises concerns about measurement accuracy; if skill efficiency gaps are this large, the results may be sensitive to how labor supply, wages, and employment are measured. Figure 2 below confirms the validity of these concerns. It shows that high-skilled workers in rich countries are more likely to be employed and work more hours, while low-skilled workers see declining employment rates. Thereofore, if traditional methods ignore employment rates and hours worked, they misrepresent the true supply of skilled vs. unskilled labor, affecting the skill efficiency estimates in Table 1. For this reason, I choose to rather present the paper's Table 2, my Table 1, as it presents robustness checks which ensure the findings in the paper's Table 1 are not driven by data limitations or measurement choices.

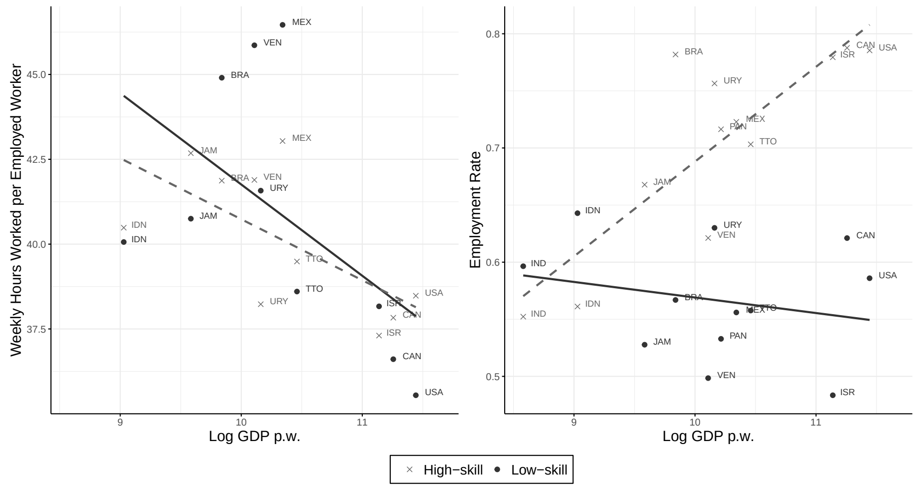

Figure 1: Hours Worked and Employment Rate by Skill Level

Notes: This figure replicates figure 2 from Rossi (2022). It 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 microdata sample. The left panel does not include India and Panama, as no data on hours worked are available for these countries. The solid (dashed) line represents the best linear fit for the low-skill (high-skill) group. The relevant code used to replicate the figure can be found here.

Below, Table 1 replicates Table 2 from the original paper. It leverages the richness of the authors micro-data to verify the extent to which gaps in relative skill efficiency reflect compositional effects and other measurement issues. The table presents estimates for elasticities of skill premium, θ_W, relative skill supply, $\theta_{\tilde{H}/\tilde{L}}$, and relative skill efficiency, θ_{AQ}, for 7 different extensions of Rossi's baseline model which allow for different sources of worker heterogeneity. Row 1 displays the results of the baseline estimation. Row 2 checks if demographic differences in experience and gender bias estimates. Row 3 tests whether excluding self-employed workers biases results. Row 4 incorporates self-employed workers' income into skill premium calculations to ensure wage-based estimates are not biased. Rows 5 to 8 compute relative skill efficiency within specific sectors to test whether results are driven by cross-country differences in sectoral structure. Lastly, columns 3 to 5 varies the assumed elasticity of substitution between 1.3, 1.5 (baseline), and 2.0, to test whether results depend on labor substitutability assumptions. These columns show that σ is inversely related to skill efficiency gaps. Overall, Table 2 confirms that the findings from Table 1 are not artifacts of measurement choices; it strengthens the argument that skill-biased technology, not just education, drives cross-country skill efficiency differences.

Table 1: Skill Premium, Supply, and Efficiency Across Countries: Robustness

	θ_W	$\theta_{\tilde{H}/\tilde{L}}$	θ_{AQ}		
			$\sigma = 1.5$	$\sigma = 1.3$	$\sigma = 1.2$
1. Baseline	-0.138	0.911	1.408	2.439	0.635
	[0.078]	[0.244]	[0.394]	[0.666]	[0.194]
2. Experience and gender	-0.024	0.796	1.52	2.549	0.748
	[0.086]	[0.249]	[0.398]	[0.673]	[0.199]
3. Baseline (self-employment sample)	-0.412	1.413	1.59	2.925	0.589
	[0.089]	[0.356]	[0.633]	[1.062]	[0.315]
4. Self-employment	-0.412	1.384	1.533	2.83	0.561
	[0.087]	[0.366]	[0.639]	[1.077]	[0.315]
5. Agriculture	-0.274	1.459	1.719	2.858	0.77
	[0.106]	[0.366]	[0.466]	[0.753]	[0.234]
6. Manufacturing	-0.209	0.9	0.952	1.615	0.399
	[0.103]	[0.272]	[0.265]	[0.446]	[0.126]
7. Low-skill services	-0.159	0.843	0.992	1.649	0.444
	[0.105]	[0.316]	[0.359]	[0.589]	[0.176]
8. High-skill services	-0.016	0.53	0.85	1.345	0.438
	[0.081]	[0.268]	[0.36]	[0.575]	[0.186]

Notes: This table replicates Table 2 from Rossi (2022). It shows the elasticities of the skill premium, relative skill supply, and relative skill efficiency with respect to GDP per worker (standard errors in brackets). The elasticities are computed using data for the 12 countries in the microdata sample, with the exceptions of rows 3 and 4 for which only the 8 countries with self-employment data are used. The code used to replicate this table can be found here.

2.2 Interpreting Relative Skill Efficiency

With the relative skill efficiency gap credibly identified, Rossi moves to understanding its drivers. He leverages available migrant data to distinguish human capital from technology effects by adding a new layer of heterogeneity, the fact that workers may have been educated in different countries. The simplified reasoning is if human capital is the main driver, migrants educated in poor countries should earn much lower skill premiums in rich countries. Whereas if technology is the main driver, migrants should have similar skill premiums as local workers in rich countries. Methodologically speaking, the production function takes the same general form as in equation (1). However, the author redefines equation (4) to,

$$H_c = \sum_a Q_{H,a} \varepsilon^a_{H,c} \tilde{H}^a_c \qquad \textit{and} \qquad L_c = \sum_a Q_{L,a} \varepsilon^a_{L,c} \tilde{L}^a_c \tag{8}$$

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 $_c$. $\varepsilon^a_{H,c}$ and $\varepsilon^a_{L,c}$ capture idiosyncratic factors affecting high- and low-skill immigrants from ^{a} in country $_c$[5]. They both equal 1 for natives. To be able to use corresponding averages among natives as population averages, Rossi assumes the foreign-educated immigrants represent a small share of the labor force. Now, in a perfectly competitive labor market, equation (3) becomes,

$$\log \frac{w^a_{H,c}}{w^a_{L,c}} = \underbrace{\log \frac{A_{H,c}}{A_{L,c}} \frac{G_H\left(A_{L,c}L_c, A_{H,c}H_c\right)}{G_L\left(A_{L,c}L_c, A_{H,c}H_c\right)}}_{\text{Country } c \text{ FE}} + \underbrace{\log \frac{Q_{H,a}}{Q_{L,a}}}_{\text{Country } a \text{ FE}} + \underbrace{\log \frac{\varepsilon^a_{H,c}}{\varepsilon^a_{L,c}}}_{\text{Pair-specific term}} \tag{9}$$

To disentangle the impact of human capital differences from technology bias effects, Rossi applies country ^{a} and country $_c$ fixed effects, separately, when running the log-wage regression (9). Then, to recover θ_Q, the author regresses the country of origin fixed effects from regression (9) on log GDP per worker. Combining this estimate with the estimate of θ_{AQ}, recovered with the same methodology as in section 2.1, allows the author to present the elasticity of human capital with respect to GDP, as well as its ratio in terms of elasticity of relative skill efficiency with respect to GDP, θ_Q/θ_{AQ}.

Results are presented below in table 2 across both a "broad" and "microdata" sample. The broad sample focuses on 102 countries of origin with at least 50 upper secondary educated and 50 tertiary educated workers in the sample. In it, θ_{AQ} is computed using educational attainment data from Barro and Lee (2013). The microdata sample only covers the 12 countries considered in section 2.1. It estimates all parameters with the same granular data. While the broad sample may seem limited, as it uses the traditional approach to compute skill premiums, it better represents global patterns, while the microdata sample is biased toward richer countries which tend to have higher relative skill efficiency. Hence, the author focuses on the broad sample as it allows for more meaningful cross-country comparisons between θ_Q and θ_{AQ}.

Row 1 presents results for the US, as this host country holds the highest variety of migrants in the sample. It establishes the baseline estimate of human capital differences explaining only about 0.10% of skill efficiency gaps. Row 2 tests the results if more host countries are added. Row 3 ensures estimates are not biased by migration patterns by controlling for shared language, geographic proximity, and colonial history between origin and host countries. Row 4 ensures skill efficiency gaps are not overestimated due to migrant selection effects. Row 5 uses only long-term migrants to test whether skill transferability affects the estimates. Row 6 uses only fluent English speakers in host countries to ensure that language barriers do not distort skill efficiency

[5] This includes selection and skill loss upon migration.

estimates. Row 7 excludes migrants who work in low-skill jobs despite having high education to test whether over-qualification biases the results. Row 8 ensures that skill efficiency gaps are not driven by industrial composition differences by controlling for differences in industry/sector employment among migrants. Row 9 controls for migrants clustering in certain regions within host countries to ensure that skill efficiency gaps are not due to local labor market conditions. Finally, columns 3 to 4 and 6 to 8 test the results sensitivity to σ, showing that it is negatively correlated with the skill efficiency gap. All robustness checks confirm that previous results are not driven by measurement issues; skill efficiency gaps are real, and they are overwhelmingly caused by technology differences, not education quality.

Table 2: Relative Human Capital Across Countries

	Broad sample (observations = 102)				Microdata sample (observations = 12)			
		θ_Q/θ_{AQ}				θ_Q/θ_{AQ}		
	θ_Q	$\sigma = 1.5$	$\sigma = 1.3$	$\sigma = 2$	θ_Q	$\sigma = 1.5$	$\sigma = 1.3$	$\sigma = 2$
1. US Immigrants	0.105	0.095	0.057	0.189	0.043	0.030	0.018	0.068
	[0.016]				[0.048]			
2. All Host Countries	0.098	0.088	0.053	0.176	0.078	0.055	0.032	0.123
	[0.016]				[0.047]			
3. Bilateral Control	0.062	0.056	0.034	0.112	0.095	0.067	0.039	0.149
	[0.026]				[0.087]			
Robustness (US immigrants)								
4. Selection Adjusted	0.039	0.035	0.021	0.070	0.067	0.047	0.027	0.105
	[0.026]				[0.08]			
5. 10+ Years in US	0.065	0.055	0.032	0.122				
	[0.06]							
6. English Speakers	0.096	0.087	0.052	0.173	0.039	0.028	0.016	0.061
	[0.015]				[0.041]			
7. Skill Downgrading	0.072	0.065	0.039	0.130	0.007	0.005	0.003	0.012
	[0.014]				[0.038]			
8. Sorting (sectors)	0.094	0.085	0.051	0.170	0.078	0.056	0.032	0.123
	[0.012]				[0.037]			
9. Sorting (geographic)	0.101	0.091	0.055	0.182	0.033	0.024	0.014	0.052
	[0.016]				[0.044]			

Notes: This table replicates Table 3 from Rossi (2022). It shows the elasticity of relative human capital with respect to GDP per capita θ_Q (standard errors in brackets) and its ratio with respect to the elasticity of relative skill efficiency θ_{AQ}. Each row reports results from a different methodology (as indicated by the row titles) to estimate the relative human capital endowment of highskill labor. The code used to replicate this table can be found here.

2.3 Implications for Development Accounting

Lastly, I present the implications of the previous findings for development accounting. The latter focuses on human capital differences as a key driver of income gaps. However, Rossi's findings suggest skill-biased technology, not human capital, drives most cross-country differences in productivity. Hence, he studies the change in income per worker if a poor country had the relative human capital of a rich country.

To answer this question, the author creates a counterfactual scenario to the standard development accounting framework. He keeps total factor productivity (TFP) and physical capital unchanged, to then give a poor country P the human capital of a rich country R and examine how much GDP per worker would increase. The counterfactual GDP for the poor country becomes,

$$y_P^* = Z_P \left[\left(A_{L,P} Q_{L,R} \tilde{L}_R \right)^{\frac{\sigma-1}{\sigma}} + \left(A_{H,P} Q_{H,R} \tilde{H}_R \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{10}$$

where all terms have previously bee defined. He then uses equation (10) and the previous equations for equilibrium skill premia to write the counterfactual GDP ratio between P and R as,

$$\frac{y_P^*}{y_R} = \frac{Q_{L,R} \tilde{L}_R}{Q_{L,P} \tilde{L}_P} \left[\frac{1 + \frac{w_{H,P} H_P}{w_{L,P} L_P} \left(\frac{y_R}{y_P} \right)^{\frac{\sigma-1}{\sigma} \theta_Q} \left(\frac{\tilde{H}_R / \tilde{L}_R}{\tilde{H}_P / \tilde{L}_P} \right)^{\frac{\sigma-1}{\sigma}}}{1 + \frac{w_{H,P} H_P}{w_{L,P} L_P}} \right]^{\frac{\sigma}{\sigma-1}} \Big/ \frac{y_R}{y_P} \tag{11}$$

where $\log \left(\frac{Q_{H,R}/Q_{L,R}}{Q_{H,P}/Q_{L,P}} \right) / \log \left(y_R / y_P \right) = \theta_Q$. Finally, he computes equation (11) using microdata from the poorest P country in the sample, India and the richest R country in the sample, the US. I present his results in Table 3, where each row computes the counterfactual GDP by considering alternative roles played by human capital. These results have two important implications.

Table 3: Relative Human Capital and Development Accounting: US vs. India

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

Notes: This table replicates Table 4 from Rossi (2022). It shows the counterfactual GDP ratio y_P^*/y_R, where P is India and R is the United States, under different calibrations of the elasticity of relative human capital θ_Q. For comparison, the actual GDP ratio in the data is $y_P/y_R = 0.057$. The code used to replicate this table can be found here.

Firstly, if a poor country like India were given the relative human capital of the US, its GDP per worker would increase only slightly ($\approx 11\%$ of US GDP). This is much lower than the approximate 70% predicted by Jones (2014), and is explained by the previous finding of human capital only accounting for 5-18% of skill efficiency gaps. Figure 2 shows these conclusions apply to poorer countries of the micro-data sample, as well as the countries at the bottom percentiles of GDP distribution in the broad sample. This has policy implications: improving education alone is not enough to close income gaps — poor countries also need technological and structural changes. Secondly, the actual skill efficiency gap is overwhelmingly explained by technology differences, not education quality. Even with the same human capital, poor countries would still lag behind rich ones because they lack the skill-biased technology, industries, and institutions to make skilled workers highly productive. This aligns with Caselli and Coleman (2006) and has policy implications: development strategies should focus on fostering industries and technologies that complement skilled labor, rather than just increasing schooling levels.

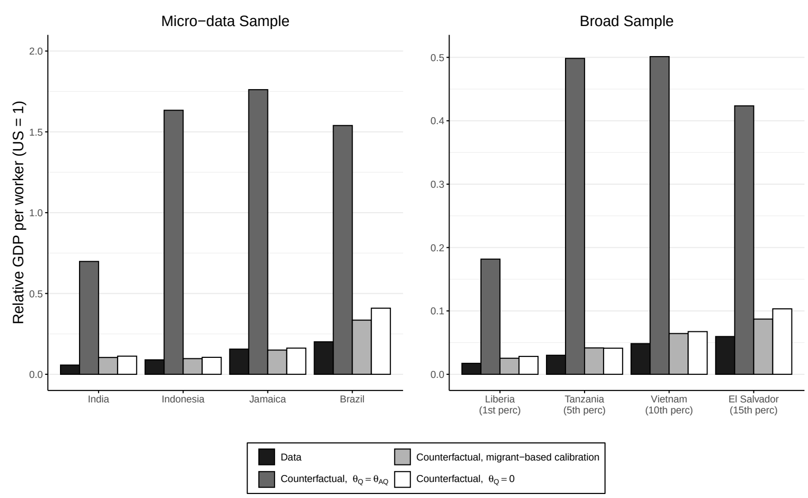

Figure 2: Relative Human Capital and Development Accounting: Selected Countries

Notes: This figure replicates Figure 8 from Rossi (2022). It plots the actual values and various counterfactuals for the GDP per worker ratio with respect to the United States. The relevant code to replicate this figure can be found here.

3 Conclusion

To conclude, Rossi (2022) fills a crucial gap in the literature by using novel micro-data to answer the disagreement between Jones (2014) and Caselli and Coleman (2006). The paper finds that cross-country differences in skilled labor productivity are driven primarily by skill-biased technology, not human capital, meaning that education alone cannot close income gaps between rich and poor countries. Going forward, future research should focus on understanding why skill-biased technology adoption varies across countries, how firms and institutions shape productivity, and whether alternative human capital measures refine our understanding of development.

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