Skilled Labor Productivity and Cross-country Income Differences

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Motivation

Development accounting:

Decompose cross-country income gaps into contributions of human capital, physical capital, ...

Recent research:

- Human capital may account for most of cross-country output gaps.
- **Imperfect substitutability** of skilled and unskilled labor is key.
- Jones (2014); Hendricks and Schoellman (2018)

Motivation

Double scarcity of skilled labor:

- Poor countries have few skilled workers.
- But the skill premium is not (much) higher than in rich countries.
- One interpretation: skilled labor is unproductive in poor countries.

Human capital is important for output gaps because poor countries lack quantity and **quality** of skilled labor.

Doubts

An implicit assumption:

Human capital is the only reason why skilled labor is less productive in poor countries.

Human capital may be far less important if we allow for other sources of skilled labor productivity differences.

- Caselli and Ciccone (2019); Jones (2019)
- Rossi (2019); Malmberg (2018)

This Paper

Revisit levels accounting when skilled labor productivity is affected by:

1. Human capital
2. Skill biased technology (Caselli and Coleman, 2006; Acemoglu, 2007)
3. Capital-skill complementarity (Krusell et al., 2000)

Our goal: estimate the contributions of all three.

Baseline Model:
No Capital-Skill Complementarity

Baseline Model

Jones (2014) meets Caselli and Coleman (2006).

From both models:

- Aggregate production function:

$$y_c = k_c^{\alpha} (z_c L_c)^{1-\alpha} \tag{1}$$

- Labor aggregator:

$$L_c = \left[\sum_{j=1}^{2} (\theta_{j,c} L_{j,c})^{\rho} \right]^{1/\rho} \tag{2}$$

From Jones (2014): $L_{j,c} = h_{j,c} N_{j,c}$.

From Caselli and Coleman (2006):

$$\sum_j [\kappa_j \theta_{j,c}]^{\omega} \leq B_c \tag{3}$$

Development Accounting

From

$$y_c = z_c \left(k_c / y_c\right)^{\alpha/(1-\alpha)} L_c \tag{4}$$

we have

$$1 = \underbrace{\frac{\ln R(z)}{\ln R(y)}}_{\text{share}_z} + \underbrace{\frac{\ln R\left(\left(k/y\right)^{\alpha/(1-\alpha)}\right)}{\ln R(y)}}_{\text{share}_k} + \underbrace{\frac{\ln R(L)}{\ln R(y)}}_{\text{share}_L} \tag{5}$$

$share_L$ combines the contributions of labor inputs and the skill bias of technology.

Notation: $R(z)$ is the rich/poor ratio z_r/z_p.

Development Accounting

How to break $share_L$ into the separate contributions of labor inputs and skill bias?

Option 1: Attribute cross-country differences in θ to labor inputs.

- Analogous to the treatment of cross-country differences in K.

Option 2: Contribution of labor inputs = change in y holding θ fixed.

For now, we pursue Option 1.

- We can derive a closed form solution for $share_L$.

Labor Aggregator

Substituting out the optimal $\theta_{j,c}$, the model implies the reduced form labor aggregator

$$L_c = \left[\sum_j \left(\kappa_j^{-1} L_{j,c} \right)^{\Psi} \right]^{1/\Psi} \tag{6}$$

where

$$\Psi = \frac{\rho\omega}{\omega - \rho} \geq \rho \tag{7}$$

Technology choice is equivalent to a higher elasticity of substitution between skilled and unskilled labor.

Implications

1. Allowing for technology choice has **no effect** on development accounting.
   The solution is the same as for a "pure" human capital model (e.g., Jones 2014).
2. Identification: the model can be estimated without separately identifying the two elasticities (ρ and ω).
   The reduced form labor aggregator only depends on Ψ.

Closed Form Solution

We can solve for $share_L$ in terms of observable data moments:

$$share_L = \underbrace{1 - \frac{\ln(wg_1)}{\ln R(y)}}_{\text{base}} + \underbrace{\left(\frac{1}{\Psi} - 1\right)\frac{\ln R(1+S(W))}{\ln R(y)}}_{\text{amplification}} \tag{8}$$

$$\Psi = \ln(RS(W))/\ln(RS(L)) \tag{9}$$

Notation:

- wg_j: wage gain due to migration (equals $w_{j,r}/w_{j,p}$).
- $W_{j,c} = w_{j,c}N_{j,c}$: labor income
- $S(W)$ is the skilled/unskilled ratio of W
- $R(1+S(W))$: poor/rich ratio of unskilled labor income share

Calibration

Data moments: 6 ▸ Details

1. output gap (1)
2. capital share (1)
3. skill premiums (2)
4. wage gains at migration (2)

Parameters to estimate: 6

1. 1 $R(z) = z_r / z_p$
2. 1 α
3. 3 $h_{j,c}$ (one normalized to 1)
4. 1 Ψ (not ρ and ω separately)

Development Accounting

	Skill Cutoff			
	SHS	HSG	SC	CG
$share_L$	0.63	0.59	0.60	0.58
Base term	0.45	0.48	0.54	0.56
Amplification term	0.19	0.12	0.06	0.02
$1/\Psi - 1$	0.15	0.28	0.24	0.33
$\frac{\ln R(1+S(W))}{\ln R(y)}$	1.27	0.42	0.26	0.07
$share_k$	0.04	0.04	0.04	0.04
$share_z$	0.33	0.37	0.36	0.38

$R(1+S(W))$: poor/rich share of unskilled labor income

Relative Skilled Labor Productivities

The goal: decompose cross-country differences in skilled labor productivity $RS(\theta h)$ into variation in h and θ.

Firm's labor demand implies

$$RS(\theta h) = RS(N)^{(1-\rho)/\rho} \tag{10}$$

$RS(N)$ is the relative abundance of skilled labor.

For conventional values of ρ (elasticities between 1.5 and 2), skilled labor is at least 5 times more productive in rich countries.

Human Capital Gaps

We can estimate $h_{j,r}/h_{j,p}$ using only data on wages and migrant wage gains.

From $w_{j,c} = p_{j,c} h_{j,c}$ we have:

$$R(h_j) = \frac{R(w_j)}{R(p_j)} = \frac{R(w_j)}{wg_j} \tag{11}$$

We find: Details

- human capital in rich countries is 2 to 3.7 times higher than in poor counties;
- relative human capital $RS(h)$ differs by at most factor 1.6.

Implications

Since $RS(h) < 1.6$ and $RS(\theta h) > 5$: skill bias gaps must be large.

At most 1/3 of relative skilled labor productivity variation is due to human capital. Details

This result is similar to Rossi (2019).

Summary: Baseline Model

1. Endogenous skill bias of technology has no effect on development accounting
   Human capital accounts for around 60% of output gaps.
2. Relative human capital (skilled vs unskilled) differs modestly across countries.
   Therefore, most of the relative skilled labor productivity gaps are due to skill bias.

Model Extensions

Exogenous Skill Bias

We consider the same model, except that skill bias parameters are taken as fixed.

Equivalently, we do not attribute changes in skill bias to $share_L$.

Definition: $share_L$ is the change in steady state output that results from replacing poor country labor inputs with rich country labor inputs, **holding $\theta_{j,c}$ fixed**.

Development Accounting

$share_L$ now depends on whether we use rich or poor country skill bias in the counterfactual.

More skill biased technology implies larger $share_L$.

With poor country skill bias:

- The effect of increasing poor country labor inputs.
- $share_L \in (0.5, 0.63)$

With rich country skill bias:

- The effect of decreasing rich country labor inputs.
- $share_L \in (0.59, 0.74)$

Details

The calibrated values of $\theta_{j,c}$ and $h_{j,c}$ are the same as with endogenous skill bias.

Capital-skill Complementarity

Model elements, based on Krusell et al. (2000):

$$y_c = s_c^{\alpha} (z_c L_c)^{1-\alpha} \tag{12}$$

$$L_c = \left[(\theta_{1,c} L_{1,c})^{\rho} + (\theta_{2,c} Z_c)^{\rho} \right]^{1/\rho} \tag{13}$$

$$Z_c = \left[(\mu_e e_c)^{\phi} + (\mu_2 L_{2,c})^{\phi} \right]^{1/\phi} \tag{14}$$

and the technology frontier.

Calibration

There is again a reduced form labor aggregator of the form

$$L_c = B_c \left([L_{1,c}/\kappa_{1,c}]^{\Psi} + [Z_c/\kappa_{2,c}]^{\Psi} \right)^{1/\Psi} \tag{15}$$

We can calibrate without separately identifying ρ and ω.

Additional data moments: ▸ Details

1. e_c/y_c, s_c/y_c from ICP
2. income share of equipment from Valentinyi and Herrendorf (2008) (assumed to be the same in rich and poor).

Development Accounting

$share_L$: Effect on steady state output of replacing poor country with rich country labor inputs, holding fixed the marginal products of equipment and structures.

Using poor country marginal products: $share_L \in (0.58, 0.65)$

Using rich country marginal products: $share_L \in (0.65, 0.70)$

Details

Decomposing Relative Productivity Gaps

We decompose $RS(\theta h)$ into the contributions of skill bias and human capital.

The contribution of h is the same as in the baseline model: $RS(h) < 1.6$.

The model implies smaller relative productivity gaps compared with the baseline.

Therefore $RS(\theta)$ is also smaller.

And the fraction of relative productivity gaps due to h is larger:

- 8% to 70% for substitution elasticities between 1.5 and 2

Conclusion

Development accounting:

1. Allowing for additional source of variation in relative skilled labor productivity does not, in general, reduce the contribution of human capital.
2. Across all models considered, human capital accounts for 50% to 75% of output gaps.

Decomposing variation in relative skilled labor productivity:

1. The contribution of human capital is modest (at most factor 1.6).
2. The contribution of technology is not robustly identified.

Data Moments

	Skill Cutoff			
	SHS	HSG	SC	CG
Skilled/unskilled employment, $S(N)$				
rich	26.16	1.13	0.35	0.06
poor	0.95	0.23	0.08	0.02
rich/poor	27.45	4.86	4.45	2.72
Skilled/unskilled wage bill, $S(W)$				
rich	71.11	3.74	1.43	0.30
poor	2.59	0.77	0.32	0.11
rich/poor	27.45	4.86	4.45	2.72
Migrant wage gain, $wg = R(p)$				
unskilled	3.71	3.46	2.98	2.84
skilled	2.29	2.21	2.08	2.04
unskilled/skilled	1.62	1.57	1.43	1.39

Estimating Relative Human Capital

	Skill Cutoff			
	SHS	HSG	SC	CG
$R(h_1)$	2.00	2.00	2.45	3.35
$R(w_1)$	7.41	6.90	7.29	9.49
wg_1	3.71	3.46	2.98	2.84
$R(h_2)$	3.24	3.12	3.51	4.65
$R(w_2)$	7.41	6.90	7.29	9.49
wg_2	2.29	2.21	2.08	2.04
$RS(h)$	1.62	1.57	1.43	1.39
$share_{h_1}$	0.29	0.29	0.38	0.51

Skill Bias Gaps

Elasticity	Skill Cutoff SHS	HSG	SC	CG
1.25	3.7	7.1	6.0	8.3
1.50	7.3	14.2	12.0	16.5
2.00	14.6	28.3	24.1	33.0
3.00	29.3	56.7	48.2	66.0
4.00	43.9	85.0	72.3	99.1
5.00	58.5	113.4	96.4	132.1

Fraction of relative skilled labor productivity gaps due to human capital.

Elasticity Implications

Our calibration implies an elasticity of substitution between skilled and unskilled labor of at least 4.

$$\frac{1}{1-\Psi} = 1 + \frac{\ln RS(N)}{\ln RS(h)} \tag{16}$$

$RS(N) > 2.7$: relative abundance of skilled labor in rich vs. poor country.

$RS(h) < 1.7$: relative human capital of skilled labor (rich vs poor country).

- can be estimated from migrant wage gains

Exogenous Skill Bias

	Skill Cutoff			
Elasticity	SHS	HSG	SC	CG
1.25	0.44	0.48	0.50	0.56
1.50	0.50	0.51	0.52	0.56
2.00	0.56	0.54	0.55	0.57
3.00	0.60	0.57	0.58	0.58
4.00	0.61	0.59	0.59	0.58
5.00	0.62	0.60	0.60	0.58
Endog. θ	0.63	0.59	0.60	0.58

Equipment and Structures Data

	s/y	e/y
Rich	2.81	0.37
Poor	2.85	0.14
Ratio	0.98	2.62

Capital-skill Complementarity

	Skill Cutoff			
	SHS	HSG	SC	CG
$share_L^{poor}$	0.65	0.61	0.62	0.58
$share_L^{rich}$	0.68	0.67	0.70	0.65
$share_{L+e}$	0.78	0.75	0.76	0.74
Elasticity	4.77	2.51	2.17	1.37

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