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

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?

Baseline:

We attribute cross-country differences in θ to labor inputs.

- $share_L$ is the contribution of human capital.
- Analogous to the treatment of cross-country differences in K.

Extension: Treat skill bias as exogenous.

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

Reduced Form Labor Aggregator

Result:

Technology choice is equivalent to increasing the elasticity of substitution between skilled and unskilled labor.

Short-run elasticity:

- governed by curvature of labor aggregator ρ
- empirical estimates commonly $1.5 - 2$

Long-run elasticity: $1/(1-\Psi)$

- captures movements along the production function and the technology frontier
- higher than short-run elasticity

Implications

1. The model is the same as a "pure" human capital model (e.g., Jones 2014),
   but with a higher elasticity of substitution.
2. **Allowing for technology choice does not alter the contribution of human capital to output gaps**
   (given calibration targets).
3. 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:

$$share_L = \text{base} + \text{amplification} \tag{6}$$

Base term = $share_L$ with perfect skill substitution:

$$\text{base} = 1 - \frac{\ln(wg_1)}{\ln R(y)} \tag{7}$$

wg_j: wage gain due to migration (equals $p_{j,r}/p_{j,p}$).
All models share the same base term (lower bound for $share_L$).

Closed Form Solution

Amplification = increase in $share_L$ due to imperfect substitution:

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

Depends on relative abundance of skilled labor and long-run elasticity:

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

Notation:

- $R(1+S(W))$: poor/rich ratio of unskilled labor income share
- $RS(W)$: rich/poor ratio of skilled/unskilled labor incomes
- $RS(L)$: relative abundance of skilled labor

Calibration

Standard data moments:

1. output gap
2. capital share
3. skill premiums

Plus wage gains at migration from Hendricks and Schoellman (2018).

▸ Details

Skilled labor: defined by education cutoff

- we consider 4 cutoffs

Development Accounting

$share_L$: $58 - 63\%$

Base: at least 45%

- all models that we consider share the same base term
- lower bound for $share_L$

Amplification: at most 19%

- long-run elasticity: $4 - 8$

▸ Details

Robust when we increase unskilled migrant wage gains.

Relative Skilled Labor Productivities

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

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

This result is similar to Rossi (2019).

Intuition:

Migrant wage gains imply that relative human capital $h_{2,c}/h_{1,c}$ does not differ greatly across countries.

Extensions

1. Exogenous skill bias
2. Investment in skill-biased technology (Acemoglu, 2007)
3. Capital-skill complementarity (Krusell et al., 2000)

Human capital accounts for $1/2$ to $3/4$ of output gaps.

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 $1/2$ to $3/4$ 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

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

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

	Skill Cutoff			
Elasticity	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.

$$\frac{1}{1-\Psi} = 1 + \frac{\ln RS(N)}{\ln RS(h)} \tag{10}$$

$RS(N) > 2.7$: 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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