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.

Result Preview

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

The human capital share depends on details:

1. Is the skill bias of technology endogenous?
   If yes: the human capital share is a robust $2/3$.
   If no: it depends on the counterfactual we want to consider.
2. Is there capital-skill complementarity?
   But quantitatively this does not matter all that much.

Baseline Model

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

Relative wages are affected by

- supply factors: relative employment and human capital
- demand factors: relative skill bias

Employment and human capital are exogenous (as usual).

Skill bias is endogenous

- a technology frontier as in Caselli and Coleman (2006) or Acemoglu (2007)

There is no capital-skill complementarity (yet).

This model is tractable - we have closed form solutions.

Model Details

From Jones (2014) and Caselli and Coleman (2006):

- 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):

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

Key Elasticities

There are two ways of substituting between skilled and unskilled labor:

1. "along" the production function – elasticity $(1-\rho)^{-1}$
2. "along" the technology frontier – "elasticity" $(1-\omega)^{-1}$

How firms respond to changes in labor supplies depends on

1. "short-run" elasticity $(1-\rho)^{-1}$
   holding technology fixed
2. "long-run" elasticity $>$ short-run elasticity
   allowing technology to adjust
   governed by both ρ and ω

Development Accounting

Aggregate production function:

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

Rich/poor ratio:

$$R(y) \equiv \frac{y_r}{y_p} = R(z) \times R\left(\left(k/y\right)^{\alpha/(1-\alpha)}\right) \times R(L) \tag{5}$$

In shares:

$$1 = \underbrace{\frac{\ln R(z)}{\ln R(y)}}_{\text{share}_z} + \underbrace{\frac{\ln R\left(\left(k/y\right)^{\alpha/(1-\alpha)}\right)}{\ln R(y)}}_{\text{share}_k} + \underbrace{\frac{\ln R(L)}{\ln R(y)}}_{\text{share}_L} \tag{6}$$

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

Development Accounting

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

One counterfactual: $share_L$ is the effect of labor inputs on output, holding technology (skill bias) fixed.

Alternative counterfactual: attribute changes in skill bias that are induced by changes in labor inputs to $share_L$

- Analogous to the treatment of cross-country differences in K.
- This is what we do in the baseline model.

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

An Identification Problem

Jones (2014): $share_L$ depends sensitively on the elasticity of substitution between skilled and unskilled labor.

Empirical evidence suggests that the "short-run" elasticity is low (1.5-2).

But its value is controversial.

Now we have to identify a second (long-run) elasticity.

How to solve this identification problem?

Reduced Form Labor Aggregator

Result:

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

Substuting out the firm's optimal technology choice yields

$$L_c = B_c \left[\sum_{j=1}^{J} \left(\kappa_j^{-1} L_{j,c} \right)^{\Psi} \right]^{1/\Psi} \tag{7}$$

with an elasticity of substitution governed by

$$\Psi = \frac{\omega\rho}{\omega - \rho} > \rho \tag{8}$$

Implications

1. Identification: the model can be estimated without separately identifying the two elasticities (ρ and ω).
   The reduced form labor aggregator only depends on Ψ.
2. The model is the same as a "pure" human capital model (e.g., Jones 2014),
   but with a higher elasticity of substitution.
3. **Allowing for technology choice does not alter the contribution of human capital to output gaps** (given calibration targets).
4. The development accounting results from the literature are **exactly correct**.

Closed Form Solution

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

$$share_L = \text{base} + \text{amplification} \tag{9}$$

Base term = $share_L$ with perfect skill substitution

- the same base term for all models that we consider

Amplification = additional contribution of human capital due to imperfect skill substitution

- positive
- base term is a lower bound for $share_L$
- differs across models that we consider

Base Term

$$\text{base} = 1 - \frac{\ln(wg_1)}{\ln R(y)} \tag{10}$$

wg_j: wage gain due to migration.

Special cases:

- no migrant wage gains: $wg_j = 1 \implies base = 1$
- migrant wage gains equal output gaps: $base = 0$

Interpreting Wage Gains

Key assumption: wage gains measure skill price ratios

$$wg_j = p_{j,r}/p_{j,p} \tag{11}$$

What could go wrong (cf. Hendricks and Schoellman (2018)):

1. Skills are not transferable across countries.
    - "doctors become cab drivers"
    - can restrict sample to workers who do not downgrade occupations
    - can impute wage gains for pre-migration occupations
2. Assimilation.
    - can restrict sample to recent / non-recent arrivals
3. Unskilled wage gains may be mismeasured.
    - few unskilled migrants from poor countries in the data
    - we show here that results are robust against changes in unskilled wg

Closed Form Solution

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

$$\text{amplification} = \left(\frac{1}{\Psi} - 1\right) \frac{\ln R(1+S(W))}{\ln R(y)} \tag{12}$$

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

$$\Psi = \ln(RS(W))/\ln(RS(L)) \tag{13}$$

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%

- roughly: $R(y) = 10.7 \approx (wg_1)^2 \implies share_L \approx 0.5$
- all models that we consider share the same base term
- lower bound for $share_L$

Amplification: at most 19%

- long-run elasticity: $4-8$
- intuition: large gaps in relative labor inputs / small gaps in skill premiums
- 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.

Result:

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.

Estimating Human Capital Gaps

If migrants are paid their marginal products, we have

$$\underbrace{R(w_j)}_{\text{observed wages}} = \underbrace{R(p_j)}_{\text{wage gains}} \times \underbrace{R(h_j)}_{h\text{ gaps}} \tag{14}$$

Therefore

$$R(h_j) = \frac{R(w_j)}{wg_j} \tag{15}$$

Note that this does not depend on the model structure.

Estimating Human Capital Gaps

	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

Human capital gaps between 2 and 4.7.

Relative h gaps $RS(h)$ at most 1.6.

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.

Exogenous Skill Bias

We remove the technology frontier and treat skill bias as exogenous.

$share_L$ measures the effect of changing human capital, holding skill bias fixed.

- At which level?

Two "natural" counterfactuals:

1. Fix skill bias at the **poor** country level.
   $share_L$ is the effect of **increasing** poor country labor inputs to rich country levels.
2. Fix skill bias at the **rich** country level.
   $share_L$ is the effect of **reducing** rich country labor inputs to poor country levels.

Results: Fixed Skill Bias

$share_L$

- ranges from 50% to 74%
- is higher when technology is more skill biased (complementarity)
- is more sensitive against variation in ρ (elasticity of substitution) for lower skill cutoffs (when relative skilled labor abundance varies more across countries).

Details

Capital-Skill Complementarity

Model:

$$y_c = s_c^{\alpha} (z_c L_c)^{1-\alpha} \tag{16}$$

$$L_c = \left[(\theta_{1,c} L_{1,c})^{\rho} + (\theta_{2,c} Z_c)^{\rho} \right]^{1/\rho} \tag{17}$$

$$Z_c = \left[(\mu_e e_c)^{\phi} + (\mu_2 L_{2,c})^{\phi} \right]^{1/\phi} \tag{18}$$

Results:

- $share_L$: not very different from the baseline case.
- skill bias gaps: smaller than in baseline case.

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

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.

$$\frac{1}{1-\Psi} = 1 + \frac{\ln RS(N)}{\ln RS(h)} \tag{19}$$

$RS(N) > 2.7$: 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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