Human Capital and Development Accounting: New Evidence from Immigrant Earnings

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UNC / ASU

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Variation in per capita income across countries: **factor 30**

How much is due to **human capital**?
Measuring Human Capital

How to measure a country’s human capital stock?

The easy part: years of schooling

- Mincer approach: $h = \exp(\phi s)$
- Klenow and Rodriguez-Clare (1997); Hall and Jones (1999)

The hard part: “school quality”
Measuring “School Quality”

GE approach
- calibrate a model of human capital production
- Erosa, Koreshkova, and Restuccia (2010); Córdoba and Ripoll (2013); Manuelli and Seshadri (2014)
- controversial: the human capital production function

Immigrant earnings approach
- Hendricks (2002); Schoellman (2012)
- controversial: migrant selection

We propose a third approach.
Our Approach

Observe wages of U.S. immigrants pre and post migration

Migrant wage gains measure cross-country wage gaps:

- pre-migration wage: \( w_c h \)
- post-migration wage: \( w_{US} h \)
- ratio: \( w_{US}/w_c \)
  measures the contribution of factors other than \( h \) to the gap in output per worker

Data: New Immigrant Survey
Focus on income gap between U.S. and countries with less than 1/4 of U.S. GDP per worker.

63% of this gap is due to human capital.

Previous results:

<table>
<thead>
<tr>
<th>Approach</th>
<th>Fraction due to $h$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mincer</td>
<td>$\approx 20%$</td>
</tr>
<tr>
<td>Immigrants</td>
<td>$\approx 30%$</td>
</tr>
<tr>
<td>This paper</td>
<td>63%</td>
</tr>
<tr>
<td>$h$ production function</td>
<td>20 – 80%</td>
</tr>
</tbody>
</table>
Contributions

A new approach for measuring country human capital stocks
No need to estimate $h$ production functions

Our approach yields estimates of **migrant selection**

- migrants from low income countries earn about 4 times more than average non-migrants
- migrants from rich countries earn roughly the same as non-migrants

Our approach yields measures of **human capital by schooling**

- relative human capital varies about uniformly across school levels
- implications for multi-skill models (Jones, 2011)
Outline

1. One skill accounting framework
2. Data: NIS
3. Results
   1. Levels accounting
   2. Migrant selection
   3. Robustness and complications
4. Multiple skill types
One Skill Model
Aggregate production function:

\[ Y_c = K_c^\alpha (A_c h_c L_c)^{1-\alpha} \]  \hspace{1cm} (1)

Equivalently:

\[ y_c = A_c (k_c/y_c)^{\alpha/(1-\alpha)} h_c \]  \hspace{1cm} (2)

\[ z_c: \text{ joint contribution of TFP and capital.} \]
Assumptions

1. Workers are paid their marginal products:

\[ w_c = \frac{\partial y_c}{\partial h_c} = (1 - \alpha) z_c \]  

2. The labor share does not vary across countries (Gollin, 2002).

3. There is one type of labor (we relax this later).
Accounting Implications

Output gap between rich and poor countries:

\[
\frac{y_{US}}{y_c} = \frac{z_{US}}{z_c} \frac{h_{US}}{h_c}
\] (4)

In logs:

\[
\Delta y_c = \Delta z_c + \Delta h_c
\] (5)

with \( \Delta y_c = \ln (y_{US}/y_c) \).

Share of the output gap due to human capital:

\[
\text{share}_{h,c} = \frac{\Delta h_c}{\Delta y_c}
\] (6)
We observe wages of U.S. immigrants

1. post migration: \( \omega_{US,c} = w_{US} h_c \alpha_c \)
2. pre migration: \( \omega_{c,c} = w_c h_c \alpha_c \)

\( \alpha_c \): migrant selection

- the \( h \) gap between immigrants and non-migrants
Measuring $h$ Gaps

The main idea:
The ratio of post to pre migration wages measures $z_{US}/z_c$.

\[
\frac{w_{US} h_c \alpha_c}{w_c h_c \alpha_c} = \frac{w_{US}}{w_c} = \text{migrant wage gain} \quad (7)
\]

\[
= \frac{z_{US}}{z_c} = \text{contribution of } z \quad (8)
\]

Human capital ratio:

\[
\frac{h_{US}}{h_c} = \frac{y_{US}}{y_c} \frac{w_c}{w_{US}}
\]

We discuss complications later (skill transferability, ...)

Measuring Migrant Selection

\[ \alpha_c = \frac{\text{median immigrant wage in } c}{\text{median non-migrant wage in } c} \]  

(9)

Imputed home country wages:

\[ \text{median wage in } c = [\text{median U.S. wage}] \times \frac{y_c}{y_{US}} \]  

(10)
Data
Nationally representative sample of new permanent residents in 2003
Surveyed between June 2003 and June 2004
Sample size: about 8,500 adults
Information on:

1. Demographic characteristics (age, sex, education)
2. Visa status
3. Current employment in U.S. \(\rightarrow w_{USh}\)
4. Last job prior to migration \(\rightarrow w_{cH}\)
Data Steps

1. Reported: wage on last pre-migration job in local currency year $t$.

2. Convert into year $t$ PPP-adjusted wage (PWT PPP factors).

3. Time shift from year $t$ to 2003 $\rightarrow$ pre-migration wage using the wage change for natives with the same [birth year, sex, education].

4. Wage gain $= \frac{\text{post-migration wage}}{\text{pre-migration wage}}$
Drop observations with

- any U.S. schooling
- last non-U.S. job before 1983
- ambiguous currencies (revaluations)

The robustness analysis deals with other complications
Group countries into bins by $y_{c,2005}$ (confidentiality).

<table>
<thead>
<tr>
<th>GDP Category</th>
<th>Most Sampled</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 1/16</td>
<td>Ethiopia, Nepal, Nigeria</td>
</tr>
<tr>
<td>1/16 – 1/8</td>
<td>India, Philippines, China</td>
</tr>
<tr>
<td>1/8 – 1/4</td>
<td>Dominican Republic, Ukraine, Bulgaria</td>
</tr>
<tr>
<td>1/4 – 1/2</td>
<td>Mexico, Poland, Russia</td>
</tr>
<tr>
<td>&gt; 1/2</td>
<td>Canada, United Kingdom, Korea</td>
</tr>
</tbody>
</table>

For each group we compute:

1. median pre- and post-migration wage
2. wage gain = [median pre migration wage] / [median post-migration wage]
3. median GDP per worker relative to the U.S. (PPP adjusted)
Results
For low income countries: $h$ accounts for $58 - 69\%$ of $\Delta y_c$.
Pre and Post Migration Wages

High pre-migration wage indicates strong migrant selection
Migrants from low income countries are strongly selected.
Migrant Selection

Direct measures of selection for lowest $y$ group:

Education:
- average years of schooling: 14.5 years
- 43% have BA degrees

Pre-migration occupations:
- majority white collar wage earners
- almost no immigrants with agricultural jobs
Potential Concerns

1. Are migrant wage gains = skill price gaps?
   1. skill transferability
   2. selection on wage gains

2. Robustness

3. Multiple skills

4. Quality of NIS wage data
   Checks to be completed
   - comparison with Census wages
   - comparison with source country non-migrant wages
Skill Transferability

Do specialized skills have value in the U.S.?
- example: a law degree from India

If not: wage gains understate skill price gaps
- our results \textit{overstate} the role of human capital
Evidence: **occupational downgrading**.

<table>
<thead>
<tr>
<th>GDP category</th>
<th>Same Occ. (Narrow)</th>
<th>Same Occ. (Broad)</th>
<th>Median Wage Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;1/16</td>
<td>6%</td>
<td>13%</td>
<td>-30%</td>
</tr>
<tr>
<td>1/16–1/8</td>
<td>26%</td>
<td>43%</td>
<td>-2%</td>
</tr>
<tr>
<td>1/8–1/4</td>
<td>10%</td>
<td>22%</td>
<td>-19%</td>
</tr>
<tr>
<td>1/4–1/2</td>
<td>9%</td>
<td>22%</td>
<td>-15%</td>
</tr>
<tr>
<td>&gt;1/2</td>
<td>32%</td>
<td>48%</td>
<td>0%</td>
</tr>
</tbody>
</table>

Most low income migrants switch to lower paid occupations after migration. Suggests that our results overstate the role of $h$. 
Skill Transferability

Table 5: Development Accounting and Skill Transfer

<table>
<thead>
<tr>
<th>Robustness Check</th>
<th>Human Capital Share</th>
<th>95% C.I.</th>
<th>Median Wage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>0.63</td>
<td>(0.55,0.71)</td>
<td>$9.00</td>
</tr>
<tr>
<td>Skill Transfer: Mean Wage</td>
<td>0.49</td>
<td>(0.42,0.56)</td>
<td>$15.59</td>
</tr>
<tr>
<td>Skill Transfer: Mean + 1 S.D. Wage</td>
<td>0.35</td>
<td>(0.27,0.42)</td>
<td>$24.37</td>
</tr>
<tr>
<td>Skill Transfer: Mean + 2 S.D. Wage</td>
<td>0.20</td>
<td>(0.12,0.28)</td>
<td>$40.73</td>
</tr>
</tbody>
</table>

Thought experiment:
Assign each occupational downgrader the median US native wage of his/her pre-migration occupation.
Selection on Wage Gains

Are migrants more likely to migrate when their home wages are low / their U.S. wages are high?

Suggestive evidence: differences between visa categories
Robustness Checks

Exclude observations with

- high inflation, unusual currencies.
- many years since last pre-migration job

Restrict observations to specific visa categories

In all cases, $h$ accounts for 52% to 70% of $y$ gaps (for countries with $y_c < 1/4y_{us}$)
Jones (2011) argues that **imperfect substitution** of high and low skill workers **amplifies** the role of $h$.

**Intuition:**
- skilled workers are scarce in low income countries
- this drives down the wages of the majority of unskilled workers

**Implications:**
- skill price gaps are small for skilled / large for unskilled workers
- especially for low income countries
Countries with $y_c < 1/4 y_{US}$

Roughly equal wage gains for skilled and unskilled workers
Consistent with the efficiency units model (perfect substitution).
Open Issues

1. Levels accounting with multiple skills.
2. Bounding the roles of skill transferability / selection on wage gains.
Confidence Intervals

Accounting Share of Human Capital

PPP GDP per worker relative to U.S., 2005

Median

95% Confidence Interval


