The Return to Cognitive Skills in the Australian Labour Market

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Returns to Education and Cognitive Skill in Australia

- Growth in earnings and income inequality, associated with increase in the skill premium
- Source: introduction of new technologies in the workplace
  - Benefit workers with greater cognitive skills
Literature Review

Studies of Wages and Cognitive Ability

- Cawley, Heckman, Vytlacil and co. (1996 - 2001)
  - NLSY data: contains Armed Forces Qualification Test (AFQT)
  - measure of cognitive ability ('general intelligence')

Key results

- Cognitive ability is significant, but modest, determinant of wages
- Important life-cycle dimension to ability formation (esp early childhood)
- Noncognitive skills acquired through schooling important
Studies of Wages and Cognitive Skill

Emphasise cognitive *skill* is a realised capacity (vs innate potential)

- **Murnane, Willet and Levy (1995):**
  - basic cognitive skill: standard mathematics test
  - return to cognitive skill increased over 1970’s & 80’s
  - factor behind increasing earning inequality

- **Blau and Kahn (2005)**
  - International Adult Literacy Survey (IALS) data for 9 countries
  - greater dispersion in literacy scores + greater reward to those skills contribute to higher wage inequality in US

- **Green and Riddell (2003):** Canadian IALS94:
  - Among FT-FY male workers, cognitive skills play a significant role
  - Returns to cognitive skills do not vary across the earnings distribution
Main Results:

- Contributions
  - Rich, contemporary Aust data; objective measures of cognitive skills; educ in yrs + qualifications
  - QR methods: examine interaction between cognitive skills and unmeasured ability

- Key Findings
  - Mean return to an additional year of education is 5.8%: 37% of which is due to measured cognitive skills acquired through schooling
  - Cognitive skills account for the negative wage gap for NESB immigrants
  - Return to cognitive skill is uniform across the conditional hourly earnings distribution
  - no interaction between cognitive skill and unmeasured ability
Data

- ABS Adult Literacy and Life Skills Survey 2006 (ALLS06)
  - profiles distribution of literacy skills, antecedents and outcomes
  - Interview randomly selected adult from household: detailed info on:
    - demographics, education
    - labour force activities, job characteristics, earnings
  - Completed a series of written tasks to gauge their proficiency in various cognitive skill domains (marked against international norms)
Four main literacy skill domains are assessed in ALLS06:

1. Prose Literacy
   - knowledge / skill needed to understand and use information from various texts (editorials, news stories and instruction manuals)

2. Document Literacy
   - knowledge / skill required to locate and use information contained in various formats (job applications, timetables, maps, tables and charts)

3. Numeracy
   - skills required to manage and respond to the mathematical demands of diverse situations (from daily living)

4. Problem Solving
   - required goal-directed thinking for which no routine solution procedure is available
• Tasks were based on real-life scenario, assess skills used in daily activities
  (Note - levels of skills tested)
• Proficiency assessed with Main Task Booklet (MTB)
  - block structure - individual tested on subset of domains
  - imputed “plausible” proficiency scores (0 to 500) in each domain
• Very high correlation in scores across domains
  \( \rho_{p,d} = 0.97, \rho_{q,ps} = 0.91, \rho_{p,ps} = 0.95 \)
⇒ Use average score across domains for each individual \((Cogn_i)\)
Selection of the analysis sample:

- **Focus:** hourly earnings in post-school, pre-retirement employment
  - Student, individuals aged less than 25 years excluded
  - Retirees, individuals aged 60+ years excluded
  - Self-employed, non-employed in prior 12 months excluded

- For “main job”: *usual hourly earnings*

- Sample restricted to full-year, full-time male workers
Limitations of Data

- Lack suitable IVs: treat key covariates as exogenous

  ⇒ use quantile regression methods to explore interaction between human capital and Cogn with unobserved ability
## Sample Means

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(<em>hourly earnings</em>)</td>
<td>3.22</td>
</tr>
<tr>
<td>Education (years)</td>
<td>13.32</td>
</tr>
<tr>
<td>Experience (years)</td>
<td>23.65</td>
</tr>
<tr>
<td>Cognitive Score</td>
<td>284</td>
</tr>
</tbody>
</table>

**Immigrant Status**

| Born overseas (ESB)        | 0.114 |
| Born overseas (NESB)       | 0.176 |
| Capital city               | 0.668 |

\[ n = 1362 \]
## Sample Means

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Job Characteristics</strong></td>
<td></td>
</tr>
<tr>
<td>Multiple Job Holder</td>
<td>0.07</td>
</tr>
<tr>
<td>Tenure (years)</td>
<td>7.31</td>
</tr>
<tr>
<td>Plant Size (workers)</td>
<td>174</td>
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<tr>
<td>Firm Size (workers)</td>
<td>475</td>
</tr>
<tr>
<td><strong>Occupation</strong></td>
<td></td>
</tr>
<tr>
<td>Blue Collar</td>
<td>0.370</td>
</tr>
<tr>
<td>White Collar</td>
<td>0.617</td>
</tr>
<tr>
<td>missing</td>
<td>0.013</td>
</tr>
<tr>
<td><em>n</em></td>
<td>1362</td>
</tr>
</tbody>
</table>
Models and Methods

- Human Capital framework linking worker skills and earnings

\[ \ln(wage_i) = F(G_{1i}, G_{2i}, G_{3i}) + \varepsilon_i \]  

where \( G_{1i} = \text{Cogn} \), \( G_{2i} = \) unmeasured cogn skills, \( G_{3i} = \) non-cogn skills,
\( \varepsilon_i = \) idiosyncratic disturbance

- Straightforward to characterise \( F(\cdot) \) if observe all \( G_{ki} \)

- Only observe inputs into these skills:

\[ G_{ki} = H_k(Educ_i, Exper_i, \theta_{ki}) \]  

where \( \theta_{ki} \) is skill-\( k \) specific ability
Models and Methods

Modeling Framework

- Approximate (2) by quadratic in \((Educ_i, Exper_i, \theta_{ki})\) and in turn approximate (1)

\[ \Rightarrow \]
Reduced form Human Capital earnings equation in \((Educ_i, Exper_i)\), ability terms unobserved and in the error term

- Coefficients: contribution of covariate to \(G_{ki}\) and how \(G_{ki}\) influences earnings

- Find quadratic terms in \(Educ, Exper\), and interaction term, insignificant (drop from specification)
Conditional Mean Hourly Earnings

- Human Capital estimating model:

\[ \ln(wage_i) = \beta_0 + \beta_1 Educ_i + \beta_2 Exper_i + u_i \]  

⇒ Coefficients measure rates of return to the human capital investments

- Add measures of skill, \( Cogn \) and other characteristics to quasi-reduced form

\[ \ln(wage_i) = \beta_0 + \beta_1 Educ_i + \beta_2 Exper_i + \beta_3 Cogn_i + \gamma X_i + u_i \]
Methods: Models for Conditional Quantile Quantile Regressions

- The $\theta$-th quantile is given by

$$\ln(wage_i) = \beta_{0}^{\theta} + \beta_{1}^{\theta} \text{Educ}_i + \beta_{2}^{\theta} \text{Exper}_i + \beta_{3}^{\theta} \text{Cogn}_i + \gamma^{\theta} X_i + u_i^{\theta}$$

- assuming $Q^{\theta}(u^{\theta}|\text{Educ}, \text{Exper}, \text{Cogn}, X) = 0$
- Marginal effects of the covariates ($\beta^{\theta}, \gamma^{\theta}$) may differ over $\theta$
- Special case: ‘pure location model’
Methods

Interpretation
Assume for simplicity $\ln(wage) = \beta_0 + \beta_1 \text{Educ} + u$

- Nonparametric approach: divide sample into cells by education
  - Percentiles of $\ln(wage)$ distribution within each cell calculated
  - Quantile regression summarises how the percentiles of the distributions change when moving from low to progressively higher education cells
  - If $u$ indexes unobserved ability, individuals with higher $\ln(wage)$ in a cell possess higher ability
  - $\beta_1^\theta$ at different $\theta$ corresponds to returns to education for individuals with different levels of ability
  - Differences in the returns reveal how ability and education interact in determining $\ln(wage)$
# Results

## WLS Conditional Mean Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)†</th>
<th>(2)†</th>
<th>(3)†</th>
<th>(4)†</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Educ</strong></td>
<td>0.058*</td>
<td>0.037*</td>
<td>0.034*</td>
<td>0.032*</td>
</tr>
<tr>
<td><strong>Exper</strong></td>
<td>0.007*</td>
<td>0.007*</td>
<td>0.007*</td>
<td>0.006*</td>
</tr>
<tr>
<td><strong>Cogn</strong></td>
<td></td>
<td>0.0026*</td>
<td>0.0023*</td>
<td>0.0021*</td>
</tr>
<tr>
<td><strong>Born overseas (ESB)</strong></td>
<td>0.044</td>
<td>0.053</td>
<td>0.059</td>
<td>0.058</td>
</tr>
<tr>
<td><strong>Born overseas (NESB)</strong></td>
<td>−0.161*</td>
<td>−0.058</td>
<td>−0.053</td>
<td>−0.056</td>
</tr>
<tr>
<td><strong>Job Characteristics</strong></td>
<td>×</td>
<td>×</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td><strong>Occupation</strong></td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>✓</td>
</tr>
<tr>
<td><strong>R²</strong></td>
<td>0.1497</td>
<td>0.1896</td>
<td>0.2203</td>
<td>0.2230</td>
</tr>
</tbody>
</table>

† Include controls for *health limitations, state of residence, capital city.*
Results

- From Model (2): $Cogn$ significant
  - $Cogn$ accounted for an additional 4% of the variation in $\ln(wage)$
  - A 1 std dev ↑ in $Cogn$ associated with 13.5% higher expected hourly earnings
  ⇒ significant reward

- From Model (2):
  - Decline in the estimated return to education to 3.7%
  ⇒ 36.6% of the return to education due to acquisition of cognitive skills with extra year of education
  - Return to experience unchanged: $Cogn$ and experience orthogonal
  - Adding $Cogn$ substantially reduced the hourly earnings ‘penalty’ for NESB immigrants
Results

- Model (3): Added tenure, plant size, firm size, multiple jobs:
  - Larger plants and firms attract a premium
  - Tenure insignificant, cet.par.

- Model (4): Added occupation
  - Blue collar jobs receive significantly lower hourly compensation
  - Some decline in estimated return to education and Cogn
Relevance of Sheepskin Effects

- Hungerford and Solon (1987): Impact of credentials beyond accumulation of yrs of education
- Important in understanding:
  - dimensions of human capital
  - functioning of labour market: learning v signaling models
  - policy interest: value of completing degrees
## Testing for ‘Sheepskin Effects’

### WLS Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)(^+)</th>
<th>(2)(^+)</th>
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</thead>
<tbody>
<tr>
<td>HS10</td>
<td>-0.0095</td>
<td>-0.0413</td>
</tr>
<tr>
<td>HS12</td>
<td>0.0570</td>
<td>-0.0244</td>
</tr>
<tr>
<td>PSCert</td>
<td>0.0526</td>
<td>0.0002</td>
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</table>

*Marginal return over HS12*

<table>
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<tr>
<th>Variable</th>
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<th>(2)(^+)</th>
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</thead>
<tbody>
<tr>
<td>PSDip</td>
<td>0.1113*</td>
<td>0.1062*</td>
</tr>
<tr>
<td>Bachelors</td>
<td>0.1910*</td>
<td>0.1596*</td>
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</tbody>
</table>

*Marginal return over Bachelors*

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)(^+)</th>
<th>(2)(^+)</th>
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</thead>
<tbody>
<tr>
<td>PostGrad</td>
<td>0.0718*</td>
<td>0.0760*</td>
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</tbody>
</table>

*Exper*  
*Educ*  
*Cogn*  

<table>
<thead>
<tr>
<th></th>
<th>(1)(^+)</th>
<th>(2)(^+)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exper</td>
<td>0.0061*</td>
<td>0.0062*</td>
</tr>
<tr>
<td>Educ</td>
<td>0.0279*</td>
<td>0.0187*</td>
</tr>
<tr>
<td>Cogn</td>
<td></td>
<td>0.0024*</td>
</tr>
</tbody>
</table>

\(R^2\)  

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>0.1919</td>
<td>0.2166</td>
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</table>
Find significant sheepskin effects ($p$-value $< 0.001$)

Add \textit{Cogn}:

- Sheepskin effects remain ($p$-value $= 0.003$)
- Substantial decline in return to secondary qualifications (beyond yrs of educ)
- Some decline in magnitude of coefficients on higher educ

$\Rightarrow$ Role of non-cognitive skills, or personality traits, associated with completion
## Quantile Regression Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>WLS</th>
<th>Conditional Quantile</th>
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<th></th>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.1</td>
<td>0.25</td>
<td>0.5</td>
<td>0.75</td>
<td>0.9</td>
<td></td>
</tr>
<tr>
<td><strong>Educ</strong></td>
<td>0.032*</td>
<td>0.019*</td>
<td>0.035*</td>
<td>0.037*</td>
<td>0.045*</td>
<td>0.044*</td>
<td></td>
</tr>
<tr>
<td><strong>Exper</strong></td>
<td>0.006*</td>
<td>0.005*</td>
<td>0.006*</td>
<td>0.005*</td>
<td>0.008*</td>
<td>0.011*</td>
<td></td>
</tr>
<tr>
<td><strong>Cogn</strong></td>
<td>0.0021*</td>
<td>0.0021*</td>
<td>0.0019*</td>
<td>0.0020*</td>
<td>0.0023*</td>
<td>0.0030*</td>
<td></td>
</tr>
<tr>
<td><strong>ESB</strong></td>
<td>0.058</td>
<td>0.051</td>
<td>0.052</td>
<td>0.084</td>
<td>0.008</td>
<td>0.072</td>
<td></td>
</tr>
<tr>
<td><strong>NESB</strong></td>
<td>−0.056</td>
<td>−0.069</td>
<td>−0.124*</td>
<td>−0.057</td>
<td>−0.060</td>
<td>−0.012</td>
<td></td>
</tr>
<tr>
<td><strong>Job Chars</strong></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td><strong>Occupation</strong></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td><strong>$R^2$</strong></td>
<td>0.2230</td>
<td>0.1222</td>
<td>0.1511</td>
<td>0.1688</td>
<td>0.1641</td>
<td>0.1418</td>
<td></td>
</tr>
</tbody>
</table>
Quantile Regressions

Coefficients significantly different across quantiles?

- Pure location model strongly rejected ($p < 0.001$)
- Equality of $\beta_{\text{educ}}^\theta$ across $\theta$ not rejected ($p = 0.06$)
- Equality of $\beta_{\text{cogn}}^\theta$ across $\theta$ not rejected ($p = 0.46$)
- Equality of $\beta_{\text{Exper}}^\theta$ across $\theta$ not rejected ($p = 0.12$)
Sheepskin Effects

- Credential dummy variables jointly significant at each quantile
  ⇒ jointly significant across the 5 quantiles considered
- Marginal return to each credential uniform across quantiles
- Including $Cogn$ substantially reduces the apparent SS effect
  ⇒ $Cogn$ fully accounts for SS effect of secondary qualifications
  and 66-75% of aggregate SS effect of post-secondary credentials
- Important role of non-cognitive skills and attributes
Conclusions

- Significant reward for Cognitive skill in the Aust labour market
  - Cognitive skills account for approx. 37% of the return to education
  - Cognitive skills orthogonal to experience
  - Differences in cognitive skill account for much of the hourly earnings ‘penalty’ for NESB immigrants

- Importance of non-cognitive skills acquired through schooling

- Return to HK and cognitive skill uniform across quantiles of the conditional hourly earnings distribution

⇒ no interaction between cognitive skill and unmeasured attributes in earnings determination

- Cognitive skills important, but not complete, explanation for ‘Sheepskin Effects’ in returns to educ