Human Capital Formation in Childhood and Adolescence

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Evolution of Inequality in USA

INCOME INEQUALITY IN THE UNITED STATES, 1910-2010

SHARE OF TOP DECILE IN NATIONAL INCOME

25% 30% 35% 40% 45% 50%

Figure
Relative Supply and Demand of Skilled Labor
Case 1: Supply and Demand Grow at Same Rate

Relative Skill Premium

Relative supply of skilled labor

Relative demand for skilled labor

Relative stocks of skills
Figure
Relative Supply and Demand of Skilled Labor
Case 1: Supply and Demand Grow at Same Rate

- Relative Skill Premium
- Relative supply of skilled labor
- Relative demand for skilled labor
- Relative stocks of skills
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Case 2: SBTC - Relative Demand Starts to Grow at a Faster Rate

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Relative Supply and Demand of Skilled Labor

Relative stocks of skills

Relative demand for skilled labor

Relative supply of skilled labor
Figure
Relative Supply and Demand of Skilled Labor
Case 2: SBTC - Relative Demand Starts to Grow at a Faster Rate
Figure
Relative Demand and Supply of Skilled Labor
Case 3: Relative Supply Starts to Grow at Slower Rate

Relative Skill Premium

Relative supply of skilled labor

Relative demand for skilled labor

Relative stocks of skills
**Figure**

Relative Demand and Supply of Skilled Labor

**Case 3: Relative Supply Starts to Grow at Slower Rate**

- **Relative Skill Premium**
- **Relative supply of skilled labor**
- **Relative demand for skilled labor**
- **Relative stocks of skills**
Figure

Relative Demand and Supply of Skilled Labor

Case 3: Relative Supply Starts to Grow at Slower Rate

- Relative supply of skilled labor
- Relative demand for skilled labor
- Relative stocks of skills
Figure

Relative Demand and Supply of Skilled Labor

Case 3: Relative Supply Starts to Grow at Slower Rate
Evolution of Inequality in USA

Figure 1
College Graduation Rates (by 35 years) for Men and Women: Cohorts Born from 1876 to 1975

Sources: 1940 to 2000 Census of Population Integrated Public Use Micro-data Samples (IPUMS).
Evolution of Inequality in USA

Figure 8.3 shows the fraction of each birth cohort with at least a high school degree, Fig. 8.3b shows the fraction of each cohort with some college attendance, and Fig. 8.3c shows the fraction of each cohort with a college degree. For additional details, see DeLong, Goldin, and Katz (2003).
Comparing across the panels shown in Fig. 8.3, it is clear that changes in college degree attainment have not followed changes in college enrollment consistently over the course of the last 25 years. While college enrollment rates have increased fairly consistently, college degree attainment declined before increasing among more recent cohorts.

Figure 8.4 presents the trend by birth cohort in the share of enrolled college students who complete a BA degree—essentially the trend shown in Fig. 8.3c divided by the trend in Fig. 8.3b. For both men and women, the rate of college completion has been below 50% for nearly a half century, with this level appreciably below the rate of completion achieved by men in the early part of the century.

A component of this stagnation has been a growing disparity in college completion rates by parental circumstances. For example, for high school students from the top quartile of the family income distribution, completion rates rose slightly from 67.4 to 71% between those starting college in the early 1980s and those starting in the early 1990s, while the college completion rates fell for students from other income groups (Bowen, Chingos, and McPherson (2009)). Indeed, for 1992 high school seniors who enrolled in college, the difference in college completion rates between the students...
Mean SAT/ACT Percentile Score of Colleges,
by Colleges' Selectivity in 1962
Evolution of Inequality in USA

1. Year of reference 2011. Countries are ranked in ascending order of the percentage-point difference between the 25-34 and 55-64 year-old population with tertiary education.

Source: OECD. Table A1.3a. See Annex 3 for notes (www.oecd.org/edu/eag.htm).

<table>
<thead>
<tr>
<th>Country</th>
<th>25-34 Tertiary Ed (%)</th>
<th>55-64 Tertiary Ed (%)</th>
<th>Difference (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Israel</td>
<td>44.50</td>
<td>46.52</td>
<td>−2.02</td>
</tr>
<tr>
<td>United States</td>
<td>44.04</td>
<td>41.81</td>
<td>2.23</td>
</tr>
<tr>
<td>Germany</td>
<td>28.96</td>
<td>26.43</td>
<td>2.52</td>
</tr>
<tr>
<td>Brazil</td>
<td>14.46</td>
<td>10.17</td>
<td>4.28</td>
</tr>
<tr>
<td>Estonia</td>
<td>39.84</td>
<td>35.50</td>
<td>4.34</td>
</tr>
<tr>
<td>Austria</td>
<td>23.03</td>
<td>16.73</td>
<td>6.29</td>
</tr>
<tr>
<td>Russian Federation</td>
<td>56.97</td>
<td>49.16</td>
<td>7.81</td>
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<tr>
<td>Finland</td>
<td>39.75</td>
<td>31.39</td>
<td>8.36</td>
</tr>
<tr>
<td>Chile 1</td>
<td>22.48</td>
<td>13.06</td>
<td>9.42</td>
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<tr>
<td>Turkey</td>
<td>21.00</td>
<td>10.32</td>
<td>10.67</td>
</tr>
<tr>
<td>Italy</td>
<td>22.25</td>
<td>11.42</td>
<td>10.83</td>
</tr>
<tr>
<td>Denmark</td>
<td>40.24</td>
<td>28.67</td>
<td>11.57</td>
</tr>
<tr>
<td>Mexico</td>
<td>24.10</td>
<td>12.51</td>
<td>11.59</td>
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<td>Switzerland</td>
<td>40.64</td>
<td>28.74</td>
<td>11.90</td>
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<tr>
<td>New Zealand</td>
<td>46.87</td>
<td>34.59</td>
<td>12.28</td>
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<tr>
<td>Canada</td>
<td>57.26</td>
<td>44.49</td>
<td>12.77</td>
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<tr>
<td>Slovak Republic</td>
<td>26.98</td>
<td>13.68</td>
<td>13.30</td>
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<tr>
<td>Iceland</td>
<td>38.38</td>
<td>24.94</td>
<td>13.44</td>
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<tr>
<td>Australia</td>
<td>47.23</td>
<td>33.03</td>
<td>14.20</td>
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<tr>
<td>Greece</td>
<td>34.74</td>
<td>20.04</td>
<td>14.71</td>
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<td>Sweden</td>
<td>43.47</td>
<td>28.66</td>
<td>14.82</td>
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<tr>
<td>Norway</td>
<td>45.02</td>
<td>29.91</td>
<td>15.11</td>
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<tr>
<td>Hungary</td>
<td>30.43</td>
<td>15.32</td>
<td>15.11</td>
</tr>
<tr>
<td>Netherlands</td>
<td>43.04</td>
<td>27.85</td>
<td>15.18</td>
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<tr>
<td>Czech Republic</td>
<td>27.83</td>
<td>12.63</td>
<td>15.20</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>47.86</td>
<td>32.62</td>
<td>15.24</td>
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<tr>
<td>Latvia</td>
<td>38.72</td>
<td>22.05</td>
<td>16.68</td>
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<td>Portugal</td>
<td>28.33</td>
<td>11.07</td>
<td>17.26</td>
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<td>Belgium</td>
<td>42.99</td>
<td>25.34</td>
<td>17.65</td>
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<td>Slovenia</td>
<td>35.36</td>
<td>17.14</td>
<td>18.22</td>
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<tr>
<td>Spain</td>
<td>39.26</td>
<td>19.02</td>
<td>20.24</td>
</tr>
<tr>
<td>France</td>
<td>42.91</td>
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<td>49.21</td>
<td>24.86</td>
<td>24.35</td>
</tr>
<tr>
<td>Japan</td>
<td>58.55</td>
<td>32.05</td>
<td>26.51</td>
</tr>
<tr>
<td>Poland</td>
<td>40.80</td>
<td>12.63</td>
<td>28.17</td>
</tr>
<tr>
<td>Korea</td>
<td>65.69</td>
<td>13.54</td>
<td>52.14</td>
</tr>
</tbody>
</table>

Figure 3
Percentage of Younger and Older Adults with Tertiary Education
Let $L_S$ and $L_U$ denote, respectively, skilled and unskilled labor.

Let $w_S$ and $w_U$ denote, respectively, skilled and unskilled wage rates.

Consider the following problem:

$$\min w_S L_S + w_U L_U$$

subject to the technology of skill formation:

$$Y = \left[ \gamma L_S^\phi + (1 - \gamma) L_U^\phi \right]^{\frac{1}{\phi}}$$

where $\gamma \in [0, 1]$ and $\phi \leq 1$. 
Taking first-order conditions:

\[ w_S = \lambda \left[ \gamma L^\phi_S + (1 - \gamma) L^\phi_U \right]^{\frac{1-\phi}{\phi}} \gamma L^{\phi-1}_S \]

\[ w_U = \lambda \left[ \gamma L^\phi_S + (1 - \gamma) L^\phi_U \right]^{\frac{1-\phi}{\phi}} (1 - \gamma) L^{\phi-1}_U \]

which yields:

\[ \ln \frac{w_S}{w_U} = \ln \frac{\gamma}{1 - \gamma} + (\phi - 1) \ln \frac{L_S}{L_U} \]
Evolution of Inequality in USA
Figure 1: The Probability of Educational Decisions, by Endowment Levels, Dropping from Secondary School vs. Graduating


James Heckman
Economics and Econometrics of Human Development
Figure 2: The Probability of Educational Decisions, by Endowment Levels, **HS Graduate** vs. College Enrollment.


James Heckman Economics and Econometrics of Human Development
Figure 3: The Probability of Educational Decisions, by Endowment Levels, **Some College vs. 4-year college degree**
Figure 4: The Effect of Cognitive and Socio-emotional endowments, (log) Wages

Figure 5: The Effect of Cognitive and Socio-emotional endowments, Daily Smoking

Figure 7: The Effect of Cognitive and Socio-emotional endowments, Participated in 2006 election
Figure 8: The Effect of Cognitive and Socio-emotional endowments on Probability of White-collar occupation (age 30)
Ever been in jail by age 30, by ability (males)


Note: This figure plots the probability of a given behavior associated with moving up in one ability distribution for someone after integrating out the other distribution. For example, the lines with markers show the effect of increasing socioemotional ability after integrating the cognitive ability.

Probability of being teenage and single with children (females)

Note: This figure plots the probability of a given behavior associated with moving up in one ability distribution for someone after integrating out the other distribution. For example, the lines with markers show the effect of increasing noncognitive ability after integrating the cognitive ability.

Gaps in Skills in Early Childhood
Hart and Risley (1995)

Figure 2. The widening gap we saw in the vocabulary growth of children from professional, working-class, and welfare families across their first 3 years of life. (See Appendix B for a detailed explanation of this figure.)
Gaps in Skills in Early Childhood
Carneiro and Heckman (2003)

Average percentile rank on anti-social behavior score, by income quartile

Score Percentile

Age

4 Yrs 6 Yrs 8 Yrs 10 Yrs 12 Yrs

Lowest Income Quartile
Second Income Quartile
Third Income Quartile
Highest Income Quartile
Gaps in Skills in Early Childhood
Casey, Lubotsky, and Paxson (2002)


Gaps in Investments in Early Childhood
Carneiro and Heckman (2003)

Figure
Unadjusted Mean Home Score
by Quartile of Permanent Income of the Family
Gaps in Investments in Early Childhood
Hart and Risley (1995)

![Graph showing words addressed to children by different types of parents over age in months.]
Gaps in Investments in Early Childhood
PSID, CDS

Investments in Human Capital of Children
by Quartiles of Permanent Income
Gaps in Investments in Early Childhood
Kalil, Ryan, and Corey (2012)


Flávio Cunha (Rice University)
Gaps in Investments in Early Childhood
Kalil, Ryan, and Corey (2012)

Gaps in Investments in Adolescence
Kalil, Ryan, and Corey (2012)

Figure 15: Parental Investment over Childhood among Whites by Mother’s Education: Material Resources

Source: Moon (2012).
Figure 16: Parental Investment over Childhood among Whites by Mother’s Education: Cognitive Stimulation

Source: Moon (2012).
Figure 17: Parental Investment over Childhood among Whites by Mother’s Education: Emotional Support

Source: Moon (2012).
Figure 18: Parental Investment over Childhood among Whites by Family Income Quartile: Cognitive Stimulation

Source: Moon (2012).
Figure 19: Parental Investment over Childhood among Whites by Family Type: Cognitive Stimulation

Source: Moon (2012).
How much, and in what ways, do kindergarten teachers matter for learning outcomes?

Two challenges:

- Sorting of students to teachers.
  - Solution: Randomly match students to teachers.
- Data on teachers are weakly correlated with student gain.
  - Improve the quality of data on teachers.
What is the CLASS and why use it?

Classroom observation tool

- Emotional support
  - Climate (positive or negative), teacher sensitivity, and regard for student perspectives
- Classroom organization
  - Behavior management, productivity, and instructional and learning formats
- Instructional support
  - Concept development, quality of feedback, and language modeling
**Example: Teacher Behaviors and CLASS Scores for Behavior Management Dimension**

Encompasses the teacher's ability to provide clear behavioral expectations and use effective methods to prevent and redirect misbehavior.

<table>
<thead>
<tr>
<th>Clear Behavior Expectations</th>
<th>Low (1,2)</th>
<th>Mid (3,4,5)</th>
<th>High (6,7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Clear expectations</td>
<td>Rules and expectations are absent, unclear, or inconsistently enforced.</td>
<td>Rules and expectations may be stated clearly, but are inconsistently enforced.</td>
<td>Rules and expectations for behavior are clear and are consistently enforced.</td>
</tr>
<tr>
<td>• Consistency</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Clarity of rules</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Proactive</th>
<th>Teacher is reactive and monitoring is absent or ineffective.</th>
<th>Teacher uses a mix of proactive and reactive responses; sometimes monitors but at other times misses early indicators of problems.</th>
<th>Teacher is consistently proactive and monitors effectively to prevent problems from developing.</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Anticipates problem behavior or escalation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Rarely reactive</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Monitoring</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Redirection of Misbehavior</th>
<th>Attempts to redirect misbehavior are ineffective; teacher rarely focuses on positives or uses subtle cues. As a result, misbehavior continues/escalates and takes time away from learning.</th>
<th>Some attempts to redirect misbehavior are effective; teacher sometimes focuses on positives and uses subtle cues. As a result, there are few times when misbehavior continue/escalate or takes time away from learning.</th>
<th>Teacher effectively redirects misbehavior by focusing on positives and making use of subtle cues. Behavior management does not take time away from learning.</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Effectively reduces misbehavior</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Attention to the positive</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Uses subtle cues to redirect</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Efficient</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Student Behavior</th>
<th>There are frequent instances of misbehavior in the classroom.</th>
<th>There are periodic episodes of misbehavior in the classroom.</th>
<th>There are few, if any, instances of student misbehavior in the classroom.</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Frequent compliance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Little aggression &amp; defiance</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Source: Pianta, La Paro & Hamre (2008)*
Break analysis in two parts:

- Estimate teacher effects: How much does it matter whether a child was assigned to teacher A or B in a school?
- Estimate the associations between within-school differences in teacher characteristics or behaviors and child learning outcomes
One standard error in teacher quality leads to increases in child learning of

- 11% of standard deviation in math.
- 13% of standard deviation in language.
- 7% of standard deviation in executive function.

Same teachers have their students learn more math and more language year after year.

- Cross-year correlation of teacher effects in math is 0.32
- Cross-year correlation of teacher effects in language is 0.42.

What explains differences in teacher effectiveness?

- One standard deviation in teacher IQ increases child’s performance by 4% of a standard deviation.
- Students randomly assigned to “rookie” teachers learn 16% of standard deviation less.
- No correlation between teacher personality scores (Big Five) and student learning.
- One standard deviation in CLASS explains 59% of a standard deviation in student learning.
- Teachers with better CLASS scores get all their students to learn more: Effects are not concentrated on girls or boys, on children with high or low levels of development when they enter school, or on children of high or low socioeconomic status.
Interestingly, parental reports of teacher quality correlate (very imperfectly) with teacher effectiveness:

- Teachers who produce one standard deviation more learning are given a 0.44 higher score (on a scale from 1 to 5).
- Rookie teachers are given 0.33 lower score by parents.
- Teachers with higher CLASS scores also get higher scores reported by parents.

However, parents do not adjust behaviors in response to differences in teacher quality:

- There is no effect on the quality or quantity of parent-child interaction at home.
- There is no effect on the child’s dropping out or absenteeism.
How teacher ratings relate to a school's poverty level

Teachers who receive the state's top value-added rating — "Most Effective" — are likely to be in schools with fewer poor students, based on value-added ratings for teachers at 1,720 public schools. Of 1,035 teachers at the wealthiest schools, 34 percent got the top rating. In contrast, of 2,411 teachers at the poorest schools, just over 9 percent were rated "Most Effective."

Source: Ohio Department of Education

Rich Exner, James Owens | The Plain Dealer
Differential susceptibility of adolescents to peer influences on Stoplight task performance

Mean (a) percentage of risky decisions and (b) number of crashes for adolescent, young adult, and adult participants when playing the Stoplight driving game either alone or with a peer audience. Error bars indicate the standard error of the mean.
Notes: Effect of schooling on components of the ASVAB. The first four components are averaged to create male’s with average ability. We standardize the test scores to have within-sample mean zero, variance one. The model is estimated using the NLSY79 sample. Solid lines depict average test scores, and dashed lines, confidence intervals. Source: Heckman, Stixrud and Urzua [2006, Figure 4].
Figure 23: Causal Effect of Schooling on Two Measures of Personality

i. Rotter Locus of Control Scale

ii. Rosenberg Self-Esteem Scale

Source: Heckman, Stixrud and Urzua [2006, Figure 5].

James Heckman
Economics and Econometrics of Human Development
Increasing Inequality in Skills
Reardon (2013)

Increasing Inequality in Skills

Social Trust
By parents' education, 12th graders, 1976–2011

“Most people can be trusted” (agree)


Upper third in parents’ education
Lower third in parents’ education

Source: Monitoring the Future
Trends in Health: Child obesity

![Graph showing trends in child obesity]

- Light gray line: HS or less
- Black line: BA or more


Percentage: 0%, 5%, 10%, 15%, 20%, 25%
Increasing Inequality in Investments
Altintas (2016)

The graph illustrates the daily minutes in developmental childcare by education level of parents.

- **Dotted line with circles**: Both parents have Bachelor’s degree or more
- **Solid line with squares**: Both parents have high school degree or less
Increasing Inequality in Investments
Kornrich and Furstenberg (2011)

Increasing Inequality in Investments

Trends in Family Dinners
By parental education, 1978–2005

"Our whole family usually eats dinner together" (agree)

Source: DDB Lifestyle surveys, 1978–2005
Increasing Inequality in Investments

Participation in School-Based Extracurriculars

1972–2002

Highest SES quartile

Lowest SES quartile

Full Circle: College Attendance

- Top quartile
- Third quartile
- Second quartile
- Bottom quartile

Data spans from 1965 to 2015.
FIGURE 7.
Share of Population with College Degree, by Income Level and Birth Year
The graduation rate for low-income individuals has not increased very much over the past few decades.

Socioeconomic Distribution at Colleges by Selectivity

A student at one of America’s most-selective universities is fourteen times more likely to be from a high-income family than from a low-income family.

Source: Carnevale and Strohl (2010).
Note: Figure shows college attendance as of 2006. See technical appendix for full description of college selectivity categories.
Application Behavior of High-Achieving Students

Panel A: High-Income Students’ Portfolios of College Applications

- Nonselective
- Less-selective

College selectivity, measured as college’s median SAT score—student’s SAT score (in percentiles)

Source: Avery and Hoxby (2012).
Evidence is Reinforced from Evidence from RCT

- Early interventions:
  - Perry Preschool Program
  - Abecedarian
  - Infant Health and Development Program (IHDP)
  - Head Start

- Interventions at School Age
  - Montreal Longitudinal Study
## Treatment Effects on Early-life Skills for Samples Pooled Across Gender

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Perry</th>
<th>ABC</th>
<th>IHDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>IQ, Age 5</td>
<td>11.422</td>
<td>6.398</td>
<td>8.475</td>
</tr>
<tr>
<td>IQ, Age 8</td>
<td>1.254</td>
<td>4.500</td>
<td>-0.671</td>
</tr>
<tr>
<td>Achievement Test Score, Ages 5–10</td>
<td>0.394</td>
<td>0.544</td>
<td>-0.012</td>
</tr>
<tr>
<td>Conscientiousness, Ages 4–7</td>
<td>0.273</td>
<td>0.047</td>
<td>0.075</td>
</tr>
<tr>
<td>Achievement Test Score, Age 27</td>
<td>1.795</td>
<td>0.422</td>
<td>0.108</td>
</tr>
</tbody>
</table>

Non-parametric permutation $p$-values account for compromised randomization, small sample size, and item non-response. See Heckman et al. (2010a) and Campbell et al. (2014, appendix) for details. Stepdown $p$-value accounts for the same and for multiple hypotheses testing. All school-age and adult achievement and conscientiousness measures have mean 0 and standard deviation 1. All IQ measures have mean 100 and standard deviation 15 and they are standardized using the national population mean and standard deviation. For PPP, IHDP, and ETP at ages 5, 3, and 7 we use the Stanford-Binet IQ test. For ABC at 5 we use the Wechsler Preschool and Primary Scale of Intelligence. For PPP and ETP at age 8 we use the Stanford-Binet IQ test. At this same age, we use Wechsler Intelligence Scale for Children for ABC and IHDP. School Age Achievement is a factor measured through a factor of items at ages 5, 6, and 7. The items analyzed come from the California Achievement Test (ABC, PPP); Metropolitan Achievement Test (ETP); Peabody Individual Achievement Test (ABC); Woodcock-Johnson Test of Achievement (ABC, IHDP). School Age Conscientiousness is a factor constructed through a battery of items from various questionnaires: Achenbach Child Behavior Checklist (ABC); Classroom Behavior Inventory (ABC); Walker Problem Behavior Identification Checklist (ABC); Teacher rating (PPP, IHDP); Reputation test (PPP, IHDP). Adult achievement is measured by Adult Performance Level (PPP); WoodcockJohnson Test (ABC); Wechsler Adult Intelligence Scale (IHDP). Adult achievement and conscientiousness measures are not available in ETP.
### Table 5: Treatment Effects on Early-life Skills for Females

<table>
<thead>
<tr>
<th>Source</th>
<th></th>
<th>Treatment Effect</th>
<th>Permutation, one-sided</th>
<th>Permutation, two-sided</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perry</td>
<td></td>
<td>IQ, Age 5</td>
<td>12.666</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td></td>
<td>IQ, Age 8</td>
<td>4.240</td>
<td>0.410</td>
</tr>
<tr>
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<td>Achievement Test Score, Ages 5–10</td>
<td>0.564</td>
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<td>Conscientiousness, Ages 4–7</td>
<td>0.515</td>
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<td>Achievement Test Score, Age 27</td>
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<td>IQ, Age 8</td>
<td>4.573</td>
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<td>Achievement Test Score, Ages 5–10</td>
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<td>Conscientiousness, Ages 4–7</td>
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<td>IHDP</td>
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<td>IQ Age 3</td>
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<td>IQ Age 8</td>
<td>-0.158</td>
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<td>Achievement Test Score Ages 5–10</td>
<td>-0.034</td>
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<td></td>
<td></td>
<td>Conscientiousness, Ages 4–7</td>
<td>0.089</td>
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<td>Achievement Test Score, Age 18</td>
<td>0.517</td>
<td>0.650</td>
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Source: Own calculations. See notes in Table 4.
Table 6: Treatment Effects on Early-life Skills for Males

<table>
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<tr>
<th>Program</th>
<th>Variable Description</th>
<th>Treatment Effect</th>
<th>Permutation, one-sided</th>
<th>Permutation, two-sided</th>
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<tr>
<td>Perry</td>
<td>IQ, Age 5</td>
<td>10.607</td>
<td>0.000</td>
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<td></td>
<td>IQ, Age 8</td>
<td>-0.721</td>
<td>0.060</td>
<td>0.250</td>
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<td>Achievement Test Score, Ages 5–10</td>
<td>0.269</td>
<td>0.000</td>
<td>0.020</td>
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<td>Conscientiousness, Ages 4–7</td>
<td>0.087</td>
<td>0.030</td>
<td>0.040</td>
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<td>Achievement Test Score, Age 27</td>
<td>0.214</td>
<td>0.110</td>
<td>0.230</td>
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<td>ABC</td>
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<td>9.962</td>
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<td>4.174</td>
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<td>0.010</td>
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<td>Conscientiousness, Ages 4–7</td>
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<td>0.590</td>
<td>0.690</td>
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<td>Achievement Test Score, Age 21</td>
<td>0.095</td>
<td>0.070</td>
<td>0.070</td>
</tr>
<tr>
<td>IHDP</td>
<td>IQ, Age 3</td>
<td>6.988</td>
<td>0.000</td>
<td>0.000</td>
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<td>IQ, Age 8</td>
<td>-1.206</td>
<td>0.450</td>
<td>0.930</td>
</tr>
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<td>Achievement Test Score Ages 5–10</td>
<td>0.012</td>
<td>0.720</td>
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<td>Conscientiousness, Ages 4–7</td>
<td>0.065</td>
<td>0.090</td>
<td>0.170</td>
</tr>
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<td></td>
<td>Achievement Test Score, Age 18</td>
<td>-0.456</td>
<td>0.500</td>
<td>0.820</td>
</tr>
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</table>

Source: Own calculations. See notes in Table 4.
Figure 2: Dynamics of IQ in PPP

(a) Standardized IQ

(b) Raw IQ

Source: Reproduced from Hojman (2015). Note: The solid line represents the trajectory of the treated group, and the dotted line represents the trajectory of the control group. Thin lines surrounding trajectories are asymptotic standard errors. It shows standardized IQ as measured by the Stanford-Binet test in each year. IQ is age-standardized based on a national sample to have a US national mean of 100 points and standard deviation of 15 points. In Figure 2b, the scores are not standardized. The scores in it represent the raw scores, or the sum of the number of correct questions in each year.

Differences by Gender

A consistent finding across all four programs is the difference in treatment effects for males and females. This difference is substantial enough to create important gender differences in both benefit-cost ratios and internal rates of return for PPP and ABC. This pattern is consistent with the literature on differences in development between girls and boys. Girls develop earlier. Uniform curricula across genders appears to benefit the laggard boys on many dimensions, but girls benefit as well, as we document in our discussion of the long-term treatment effects of ABC and PPP. In addition, all programs (except IHDP) target ages 3–4 when aggressive behavior that predicts adult aggression and participation in crime begins to manifest itself (White et al., 1994). Gender-specific curricula in preschool may be an appropriate strategy.

Table 7: Life-Cycle Outcomes, PPP and ABC

<table>
<thead>
<tr>
<th></th>
<th>PPP</th>
<th></th>
<th>ABC</th>
<th></th>
</tr>
</thead>
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<tr>
<td></td>
<td>Age Female</td>
<td>Male</td>
<td>Age Female</td>
<td>Male</td>
</tr>
<tr>
<td>Cognition and Education</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Adult IQ</td>
<td>-</td>
<td>-</td>
<td>21&lt;sup&gt;c&lt;/sup&gt;</td>
<td>10.275</td>
</tr>
<tr>
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<td></td>
<td></td>
<td>(0.005)</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td></td>
<td>2.588</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.130)</td>
</tr>
<tr>
<td>High School Graduation</td>
<td>19&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.56 (0.000)</td>
<td>0.02 (0.416)</td>
<td>21&lt;sup&gt;c&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
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<td>(0.100)</td>
</tr>
<tr>
<td>Economic</td>
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<td></td>
</tr>
<tr>
<td>Employed</td>
<td>40&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.01 (0.615)</td>
<td>0.29 (0.011)</td>
<td>30&lt;sup&gt;c&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
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<td>(0.302)</td>
</tr>
<tr>
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<td></td>
<td>(0.050)</td>
</tr>
<tr>
<td>Yearly Labor Income, 2014 USD</td>
<td>40&lt;sup&gt;a&lt;/sup&gt;</td>
<td>$6,166 (0.224)</td>
<td>$8,213 (0.150)</td>
<td>30&lt;sup&gt;c&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(17,214)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.110)</td>
</tr>
<tr>
<td>HI by Employer</td>
<td>40&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.129 (0.055)</td>
<td>0.206 (0.103)</td>
<td>31&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
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<td>(0.296)</td>
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<td>(0.035)</td>
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<tr>
<td>Ever on Welfare</td>
<td>18–27&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.27 (0.049)</td>
<td>0.03 (0.590)</td>
<td>30&lt;sup&gt;c&lt;/sup&gt;</td>
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<td></td>
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<td>(0.000)</td>
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<tr>
<td>Crime</td>
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<tr>
<td>No. of Arrests&lt;sup&gt;d&lt;/sup&gt;</td>
<td>≤40&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-2.77 (0.041)</td>
<td>-4.88 (0.036)</td>
<td>≤34&lt;sup&gt;c&lt;/sup&gt;</td>
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<td>No. of Non-Juv. Arrests&lt;sup&gt;d&lt;/sup&gt;</td>
<td>≤40&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-2.45 (0.051)</td>
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<td>One-sided permutation</td>
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<td>Lifestyle</td>
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<tr>
<td>Self-reported Drug User</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>30&lt;sup&gt;c&lt;/sup&gt;</td>
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<td>(0.030)</td>
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<td>Not a Daily Smoker</td>
<td>27&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.111 (0.110)</td>
<td>0.119 (0.089)</td>
<td>-</td>
</tr>
<tr>
<td></td>
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<td>-</td>
</tr>
<tr>
<td>Not a Daily Smoker</td>
<td>40&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.067 (0.206)</td>
<td>0.194 (0.010)</td>
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</tr>
<tr>
<td>Physical Activity</td>
<td>40&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.330 (0.002)</td>
<td>0.090 (0.545)</td>
<td>21&lt;sup&gt;b&lt;/sup&gt;</td>
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<td>(0.086)</td>
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<td>Health</td>
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<tr>
<td>Obesity (BMI &gt;30)</td>
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<td>-</td>
<td>-</td>
<td>30–34&lt;sup&gt;c&lt;/sup&gt;</td>
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<tr>
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<td></td>
<td>(0.292)</td>
</tr>
</tbody>
</table>

Figure 3: Decompositions of Treatment Effects of PPP on Male Adult Outcomes

- CAT total at age 14, end of grade 8 (0.566*)
- # of misdemeanor arrests, age 27 (-1.21**)
- # of felony arrests, age 27 (-1.12)
- # of adult arrests (misd.+fel.), age 27 (-2.33**)
- Monthly income, age 27 (0.876**)
- Use tobacco, age 27 (-0.119*)
- # of adult arrests (misd.+fel.), age 40 (-2.33**)
- # of felony arrests, age 40 (-1.14*)
- # of misdemeanor arrests, age 40 (-3.13**)
- # of lifetime arrests, age 40 (-4.20*)
- Employed, age 40 (0.200**)

Source: Reproduced from Heckman et al. (2013). See note in Figure 3.

Figure 3: Decompositions of Treatment Effects of PPP on Male Adult Outcomes

- Employed, age 40 (0.200**)
- # of lifetime arrests, age 40 (-4.20*)
- # of adult arrests (misd.+fel.), age 40 (-4.26**)
- # of felony arrests, age 40 (-1.14*)
- # of misdemeanor arrests, age 40 (-3.13**)
- Use tobacco, age 27 (-0.119*)
- Monthly income, age 27 (0.876**)
- # of adult arrests (misd.+fel.), age 27 (-2.33**)
- # of felony arrests, age 27 (-1.12)
- # of misdemeanor arrests, age 27 (-1.21**)
- CAT total at age 14, end of grade 8 (0.566*)

Cognitive Factor
- Externalizing Behavior
- Academic Motivation
- Other Factors

Source: Reproduced from Heckman et al. (2013). Note: The total treatment effects are shown in parentheses. Each bar represents the total treatment effect normalized to 100 percent. One-sided p-values are shown above each component of the decomposition. See the Web Appendix of Heckman et al. (2013) for detailed information about the simplifications made to produce the figure. "CAT total" denotes California Achievement Test total score normalized to control mean 0 and variance of 1. Asterisks denote statistical significance: * – 10% level; ** – 5% level; *** – 1% level. Monthly income is adjusted to thousands of 2006 dollars using annual national CPI.

Figure 4: Decompositions of Treatment Effects of PPP on Female Adult Outcomes

- Months in all marriages, age 40 (39.6*)
- # of lifetime violent crimes, age 40 (-0.574**)
- # of felony arrests, age 40 (-0.383**)
- # of misdemeanor violent crimes, age 40 (-0.537**)
- Ever tried drugs other than alcohol or weed, age 27 (-0.227**)
- Jobless for more than 1 year, age 27 (-0.292*)
- # of misdemeanor violent crimes, age 27 (-0.423**)
- Mentally impaired at least once, age 19 (-0.280**)
- Any special education, age 14 (-0.262**)
- CAT total, age 14 (0.806**)
- CAT total, age 8 (0.565*)
- CAT total, age 14 (0.806**)

Cognitive Factor
- Externalizing Behavior
- Academic Motivation
- Other Factors

Source: Reproduced from Heckman et al. (2013). See note in Figure 3.
Table 9: Evidence Across Studies of the Impacts of Head Start

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<td>Dataset</td>
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<td>PSID AA, mother</td>
<td>Multiple</td>
<td>C-NLSY AA</td>
<td>C-NLSY Males</td>
<td>HSIS</td>
<td>HSIS</td>
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<td>Subpopulation</td>
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<td>(Various sources)</td>
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<td></td>
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<tr>
<td>IQ/achievement, ages 3-4</td>
<td>-0.031</td>
<td>-0.552</td>
<td>0.46</td>
<td>-0.008</td>
<td>-0.647</td>
<td>0.46</td>
<td></td>
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<td>IQ/achievement, ages 5-6</td>
<td>0.230</td>
<td>0.084</td>
<td>(0.038)</td>
<td>0.300</td>
<td>(0.147)</td>
<td>(0.05)</td>
<td>-</td>
</tr>
<tr>
<td>IQ/achievement, ages 7-21</td>
<td>0.375</td>
<td>(0.047)</td>
<td>(0.151)</td>
<td>0.127</td>
<td>(0.227)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Grade retention ever</td>
<td>-0.008</td>
<td>-</td>
<td>-</td>
<td>-0.126</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>High School Grad. (no GED)</td>
<td>-</td>
<td>0.09</td>
<td>0.117</td>
<td>0.067</td>
<td>(0.095)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Attended some college</td>
<td>-</td>
<td>0.031</td>
<td>0.028</td>
<td>0.136</td>
<td>(0.076)</td>
<td>-</td>
<td>-</td>
</tr>
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<td>Earnings, ages 23-40</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.017</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Idle</td>
<td>-</td>
<td>0.051</td>
<td>(0.0357)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Ever booked crime</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.126</td>
<td>-</td>
<td>0.647</td>
<td>-</td>
</tr>
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<td>Behavior Index, ages 12-13</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.051</td>
<td>-</td>
<td>0.582</td>
<td>-</td>
</tr>
<tr>
<td>Depression Scale, ages 16-17</td>
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<td>-</td>
<td>-</td>
<td>-0.552</td>
<td>-</td>
<td>0.489</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: Impacts predicted at this age is not reported. Our calculations use bootstrapped standard errors. Grade retention is measured at age 5 in Currie and Thomas (1995) and at age 18 in all other studies. Earnings in Garces et al. (2002) are measured in logs. Ludwig and Miller (2007) use census data, Vital Statistics, and the NELS. For the sake of brevity, we limit the number of estimates we present from Ludwig and Miller (2007) to only one per data set: the impact of treatment on mortality is from the Vital Statistics, impact on high school completion is from the NELS, and impact on attending some college is from the census. Impact on high school completion and college attendance are for children roughly 18-24 years old. Feller et al. (2014) originally reported 95% posterior intervals of 0.15, 0.30 during the Head Start Program. Impacts reported in Kline and Walters (2014) are estimated from a summary index created from Peabody Picture Vocabulary Tests and Woodcock-Johnson III Preacademic Skills tests taken in Spring 2003; this index is standardized to have mean 0 and a standard deviation of 1. The Center for Epidemiological Studies Depression Scale in Carneiro and Ginja (2014) measures symptoms of depression in percentile scores, where higher scores are negative. AA: African-American. For IQ in Zhai et al. (2014), we report effect sizes on PPVT at ages 3 and 4 (they coincide). For behavior we report hyperactiveness at these same ages. Only Zhai et al. (2014) accounts for multiple hypotheses testing, across similar outcomes. For the studies using HSIS data, all treatment effects are reported in terms of effect sizes and, thus, are comparable across studies. For the estimation results that are reported separately for 3-year-old and 4-year-old cohorts, we use simple averages. For ages 3–4, we report the results in Feller et al. (2014), Kline and Walters (2014) and Zhai et al. (2014), measured after the Head Start year. For ages 5–6, we report the results in Zhai et al. (2014) measured after the children finish kindergarten. The comparable results in Puma et al. (2012) are 0.135 for ages 3–4 and 0.085 for ages 5–6. Impacts are reproduced from the Web Appendix for Elango et al. (2015). IQ is reported at age 3 using the Stanford-Binet Intelligence Scale. Grade retention is reported for K-12 schooling. High school graduation is reported at age 19. Income is reported at age 30 in 2014 dollars. "Ever booked crime" represents total arrests by age 34.
Table 4

Treatment effects on IQ z-score by low-income status using IHDP HLBW sample with ECLS-B weights.

<table>
<thead>
<tr>
<th>Outcome (sample size)</th>
<th>Treatment</th>
<th>Low income</th>
<th>Treatment x (Low income)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age 1 IQ (n=330)</td>
<td>0.109 (0.132)</td>
<td>-0.037 (0.122)</td>
<td>0.097 (0.253)</td>
</tr>
<tr>
<td></td>
<td>0.112 (0.133)</td>
<td>-0.072 (0.171)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.065 (0.177)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 2 IQ (n=322)</td>
<td>0.793*** (0.160)</td>
<td>-0.875*** (0.244)</td>
<td>0.872** (0.280)</td>
</tr>
<tr>
<td></td>
<td>0.878*** (0.223)</td>
<td>-1.181*** (0.270)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.433* (0.219)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 3 IQ (n=328)</td>
<td>0.903*** (0.147)</td>
<td>-1.017*** (0.181)</td>
<td>1.482*** (0.210)</td>
</tr>
<tr>
<td></td>
<td>1.001*** (0.181)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.323 (0.210)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Coefficient significance (within site correlation corrected standard errors): *0.10, **0.05, ***0.01.

All models also condition on child gender, birth weight, gestational age at birth, neonatal health index and site indicators. Estimates in appendix.
Fig. 1. Example of an Experimental (a) and a Control trial (b) in the Director condition. Note. The participant heard the instruction: ‘Move the small ball left’ from the director. Experimental trial (a): if the participant ignored the director’s perspective he would move the distractor ball (golf ball, cannot be seen by the director), which is the smallest ball in the shelves instead of the larger target ball (tennis ball) that is visible from the participant’s and the director’s perspective. In the Control trial (b), an irrelevant object (plane) replaces the distractor item.
Figure 1. **Non-cognitive skills and school performance during adolescence.** A, B and C show distributions for non-cognitive skills measured in early adolescence for the control, treatment and non-disruptive groups (the non-disruptive boys being those who were not disruptive in kindergarten and did not participate in the experiment as treatment or control: they serve as a normative population baseline). Kolmogorov-Smirnov test for equality of Treatment and Control distributions gives p-value of 0.003 for Trust, 0.036 for Aggression Control, and 0.023 for Attention-Impulse Control. D shows the increasing gap in the percent of subjects held back at each age. P-value from $\chi^2$ test between Treatment and Control groups is 0.60 at age 10 and 0.01 at age 17.
Figure 2. Young Adult Outcomes. As young adults, treatment subjects commit fewer crimes, are more likely to graduate from secondary school, are more likely to be active fulltime in school or work, and are more likely to belong to a social or civic group. The intervention closed part or all of the gap between boys ranked as disruptive in kindergarten but not treated (the control group) and the non-disruptive boys (who represent the normative population). Raw differences are significant for secondary diploma (p-value=0.04) and group membership (p-value=0.05), conditional differences (controlling for group imbalances) are significant for number of crimes (p-value=0.09) and percent active fulltime (p-value=0.03).
Figure 3. School achievement explained by IQ and non-cognitive skills. The non-cognitive skills measured in this paper explain a higher proportion of school performance than IQ. The bars plot the adjusted R-squared from uncontrolled OLS regressions of IQ or non-cognitive skills (Trust, Aggression Control, and Attention-Impulse Control), or both, on different measures of school achievement.
Figure 4. Proportion of impact on Grades and Young Adult Outcomes explained by Aggression Control, Attention-Impulse Control, and Trust. Increases in non-cognitive skills explain a substantial portion of the impact on several outcomes. Calculated percentages and p-values presented in Supplementary materials section F.
Next, I will try to make sense of this data by proposing a very simple model of human capital formation.

At the core of this model, there will be two important parameters:

- **Self-productivity of skills**: I learn how to read, then I use reading to learn other skills.
- **Dynamic complementarity**: The returns to the development of advanced skills are higher for the individuals who learned basic skills.
Consider the following cost minimization problem:

$$\min x_E + \frac{1}{1+r} x_L$$

subject to the technology of skill formation:

$$h = \left[ \gamma x_E^\phi + (1 - \gamma) x_L^\phi \right]^{\frac{1}{\phi}}$$

where $\gamma \in [0, 1]$ and $\phi \leq 1$.

Note that:
- The parameter $\gamma$ captures self-productivity.
- The parameter $\phi$ captures dynamic complementarity.
Boundary Solution when $\phi = 1$

- In this case, $h = \gamma x_E + (1 - \gamma) x_L$.
- Two investment strategies: Invest early and produce $\gamma$ units of human capital per unit of investment.
- Save in physical assets early and invest $1 + r$ late and produce $(1 + r)(1 - \gamma)$ units of human capital.
- Should invest all early if, and only if:

$$\gamma > \frac{1 + r}{2 + r}$$
Boundary Solution when $\phi \to -\infty$

- In this case, $h = \min \{x_E, x_L\}$
- The solution to this problem is $x_E = x_L$ for whatever values of $r$. 
Interior Solution when $-\infty < \phi < 1$

The solution to this problem is:

$$x_E = \frac{\gamma^{\frac{1}{1-\phi}}}{\left[\gamma^{\frac{1}{1-\phi}} + (1-\gamma)^{\frac{1}{1-\phi}} (1+r)^{\frac{\phi}{1-\phi}}\right]^\frac{1}{\phi}} h$$

$$x_L = \frac{(1-\gamma)^{\frac{1}{1-\phi}} (1+r)^{\frac{1}{1-\phi}}}{\left[\gamma^{\frac{1}{1-\phi}} + (1-\gamma)^{\frac{1}{1-\phi}} (1+r)^{\frac{\phi}{1-\phi}}\right]^\frac{1}{\phi}} h$$

Note that we have the following ratio:

$$\ln \frac{x_E}{x_L} = \frac{1}{1-\phi} \ln \left(\frac{\gamma}{1-\gamma}\right) + \frac{1}{1-\phi} \ln \left(\frac{1}{1+r}\right)$$
Figure 2: The Ratio of Early to Late Investment in Human Capital

As a function of the skill multiplier for different values of complementarity.

Leontief: $I = -0.5$

Cobb-Douglas: $I = 0.5$

This figure shows the optimal ratio of early to late investments, $L_1/L_2$, as a function of the skill multiplier parameter $\gamma$ for different values of the complementarity parameter $\phi$, assuming that the interest rate $r$ is zero.

The optimal ratio $L_1/L_2$ is the solution of the parental problem of maximizing the present value of the child's wealth through investments in human capital, $k$, and transfers of risk-free bonds. Let $t$ denote the present value as of period 3 of the future prices of one efficiency unit of human capital:

$$t = \frac{P}{W_{w=3} z_w (1 + u)^{w=2}}$$

The parents solve:

$$\max \sum \mu_1 1 + u \left[ t_k + e \right]$$

subject to the budget constraint:

$$L_1 + L_2 (1 + u) + e (1 + u)^2 = P$$

and the technology of skill formation:

$$k = h L_1 + (1 - \phi) L_2$$

for $0 \leq \phi \leq 1$ and $\phi = 1$.

From the first-order conditions it follows that:

$$L_1/L_2 = h (1 + u) \gamma_1$$

This ratio is plotted in this figure when $\phi = 0$, $\phi = 0.5$, and $\phi = 5$ and for values of the skill multiplier between 0 and 0.9.

(Assumes $r = 0$)

Source: Cunha et al. (2007, 2009).
Dual Side of Dynamic Complementarity

- Returns to late investments are higher for the individuals that have high early investments.
- BUT
- Returns to early investments are higher for the individuals who will also have high late investments.
- In other words, if the child will not receive high late investments, then the impacts of early investments will be diminished.
There are $S$ different developmental stages: $s = 1, \ldots, S$. The technology for skill $k$, at period $t$ and stage $s$ is:

$$\theta_{k,t+1} = e^{\eta_{c,t+1}} \times f_{s,k}$$

where

$$f_{s,k} = [\gamma_{s,k,1} \theta_{c,t} + \gamma_{s,k,2} \theta_{n,t} + \gamma_{s,k,3} \phi_{k,t} + \gamma_{s,k,4} \theta_{c,p} + \gamma_{s,k,5} \theta_{n,p}] \frac{1}{\phi_{s,c}}$$
### Table V

The Technology for Cognitive and Noncognitive Skill Formation
Estimated Along With Investment Equation With Linear Anchoring on Educational Attainment (Years of Schooling); Factors Normally Distributed

Panel A: Technology of Cognitive Skill Formation (Next Period Cognitive Skills)

<table>
<thead>
<tr>
<th>Current Period Cognitive Skills (Self-Productivity)</th>
<th>First Stage Parameters</th>
<th>Second Stage Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_{1,C,1}$</td>
<td>0.426</td>
<td>$\gamma_{2,C,1}$</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>Current Period Noncognitive Skills (Cross-Productivity)</td>
<td>$\gamma_{1,C,2}$</td>
<td>0.127</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td></td>
</tr>
<tr>
<td>Current Period Investments</td>
<td>$\gamma_{1,C,3}$</td>
<td>0.322</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td></td>
</tr>
<tr>
<td>Parental Cognitive Skills</td>
<td>$\gamma_{1,C,4}$</td>
<td>0.059</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>Parental Noncognitive Skills</td>
<td>$\gamma_{1,C,5}$</td>
<td>0.066</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td></td>
</tr>
<tr>
<td>Complementarity Parameter</td>
<td>$\phi_{1,C}$</td>
<td>0.748</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td></td>
</tr>
<tr>
<td>Implied Elasticity Parameter</td>
<td>$1/(1-\phi_{1,C})$</td>
<td>3.968</td>
</tr>
<tr>
<td>Variance of Shocks $\eta_{C,t}$</td>
<td>$\delta_{1,C}^2$</td>
<td>0.159</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td></td>
</tr>
</tbody>
</table>
Panel B: Technology of Noncognitive Skill Formation (Next Period Noncognitive Skills)

<table>
<thead>
<tr>
<th>Current Period Cognitive Skills (Cross-Productivity)</th>
<th>First Stage Parameters</th>
<th>Second Stage Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \gamma_{1,N,1} )</td>
<td>0.000</td>
<td>( \gamma_{2,N,1} )</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>Current Period Noncognitive Skills (Self-Productivity)</td>
<td>( \gamma_{1,N,2} )</td>
<td>0.712</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>Current Period Investments</td>
<td>( \gamma_{1,N,3} )</td>
<td>0.195</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>Parental Cognitive Skills</td>
<td>( \gamma_{1,N,4} )</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td>Parental Noncognitive Skills</td>
<td>( \gamma_{1,N,5} )</td>
<td>0.093</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>Complementarity Parameter</td>
<td>( \phi_{1,N} )</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>(0.27)</td>
<td></td>
</tr>
</tbody>
</table>

Elasticity Parameter

\[
\frac{1}{1 - \phi_{1,N}} \quad 1.017 \quad \frac{1}{1 - \phi_{2,N}} \quad 0.756
\]

Variance of Shocks \( \eta_{N,t} \)

\[
\delta^2_{1,N} \quad 0.170 \quad \delta^2_{2,N} \quad 0.104
\]

Note: Standard errors in parenthesis.
Interpretation of Findings: Maximizing Average Education

- Suppose that $H$ children are born, $h = 1, \ldots, H$.
- These children represent draws from the distribution of initial conditions $F(\theta_{c,1,h}, \theta_{n,1,h}, \theta_{c,p}, \theta_{n,p}, \pi)$.
- We want to allocate finite resources $B$ across these children for early and late investments.
- Formally:

$$S^* = \max \frac{1}{H} \left[ \sum_{h=1}^{H} S(\theta_{c,3}, \theta_{n,3}, \pi_{h}) \right]$$

subject to the technologies for the formation of cognitive and noncognitive skills as well as:

$$\sum_{h=1}^{H} (x_{1,h} + x_{2,h}) = B$$
Another possibility is to minimize aggregate crime (average crime per individual).

This will lead to different optimal ratios as crime is more sensitive to changes in noncognitive skills.

Relative to cognitive skills, noncognitive skills are more malleable at later ages.
Figure 6.—Densities of ratio of early to late investments maximizing aggregate education versus minimizing aggregate crime.
Figure 5A
Share of Residual Variance in Measurements of Investments Due to the Variance of Investment Factor (Signal) and Due to the Variance of Measurement Error (Noise)
Figure 5B
Share of Residual Variance in Measurements of Investments
Due to the Variance of Investment Factor (Signal)
and Due to the Variance of Measurement Error (Noise)

Musical Instruments Ages 9-10
Museum Ages 9-10
Eats with Mom/Dad Ages 9-10
Mom Reads to Child Ages 9-10
Books Ages 9-10
Encouragement Ages 7-8
Praises Ages 7-8
Family Gatherings Ages 7-8
Musical Shows Ages 7-8
Special Lessons Ages 7-8
Daily Newspapers Ages 7-8
Musical Instruments Ages 7-8
Museum Ages 7-8
Eats with Mom/Dad Ages 7-8
Mom Reads to Child Ages 7-8
Books Ages 7-8
Encouragement Ages 5-6
Praises Ages 5-6
Family Gatherings Ages 5-6
Musical Shows Ages 5-6
Special Lessons Ages 5-6
Daily Newspapers Ages 5-6
Musical Instruments Ages 5-6
Museum Ages 5-6
CD player Ages 5-6

Percentage
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Signal  Error
Figure 5C
Share of Residual Variance in Measurements of Investments Due to the Variance of Investment Factor (Signal) and Due to the Variance of Measurement Error (Noise)
Home Observation for the Measurement of the Environment

- Created by Bettye Caldwell and Robert Bradley in late 1960s, early 1970s (first published in 1980s)
- Evaluates a child’s home environment as well as parent-child interaction.
- Administered by trained professional at the child’s home with both child and primary caregiver present.
- Semi-structured interview and observation period: 45-60 minutes.
HOME: Strengths and Weaknesses

**Strengths**
- Easy to administer and score.
- Reliability and validity.
- Easy to adapt for specific purposes.
- Provides objective information on home, child, and parent-child interaction.

**Weaknesses:**
- Training of administrators to follow standardized measurement.
- Only Yes/No questions.
- Score: Simple summation gives “too much” weight to items that do not vary a lot across households.
Let $\theta_i$ denote the latent quality of the environment experienced by child $i$.

Let $d_{i,j}^* = a_j (\theta_i - b_j) + \epsilon_{i,j}$ and define $d_{i,j} = 0$ if $d_{i,j}^* \leq 0$ and $d_{i,j} = 1$, otherwise.

Assume $\epsilon_{i,j}$ has logistic distribution and let $\theta_i$ be normally distributed with mean zero and variance $\sigma^2$.

Parameter $a_j$ is item discrimination while $b_j$ is item difficulty.
Interpretation of IRT Parameters

Section 5: The two-parameter logistic (2PL) model

The same is true of the symbol $a$ since slopes are usually denoted with $b$ in statistics.

We saw on Figure 6 that the IRF in a 1PL model run parallel to each other and never cross; different difficulty parameters solely shift the curve to the left or to the right while its shape remains unchanged.

$P_i(\theta; b_i; a_i)$

Figure 13: The item response functions of three 2PL items

What about the green curve? It has the same slope as the black one but it is shifted to the right — hence the item with the green curve has the same discrimination parameter as the item with the black curve. The discrimination parameters $a_i$ are sometimes called slope parameters, just like the item difficulties are a.k.a. location parameters. The slope of the 2PL item response function at $b$ is equal to $a$.

Figure 13: The item response functions of three 2PL items
Properties of an Informative IRT Scale

Informative Scale

Probability

Theta

-4 -2 0 2 4

0 .5 1
Properties of an Informative IRT Scale: TCC
Properties of an Informative IRT Scale: TIF

Informative Scale

- Test information
- Standard error

Theta

Information

Standard Error

0

15

-4

4

0

5

10

15
HOME: IRT Analysis

- In few words, an informative scale (as presented in the last four graphs) would have items that have good discriminatory power as well as variability in difficulty.
- This combination allows us to identify, with a lot of precision, households that have low, medium, and high quality environments.
- Unfortunately, the HOME Scale does not have this property.
- As I will show below, that are “too many” easy items and “too few” medium and difficult items.
- For this reason, the HOME Scale will be able to separate very low quality home environments from okay ones, but it will not have power to separate okay from great home environments.
IRT Properties of Full Scale HOME

Item Characteristic Curve - All Items

PHD Study

Probability

Theta
IRT Properties of Full Scale HOME

Item Information Function - All Items

PHD Study

Information

Theta

0

-4

-2

0

2

4

15

10

5

0

1

2

3

4
Test Characteristic Curve of the HOME Scale - All Items

PHD Study

Expected Score

Theta

0

12.4

28.3

35.1

37.4

40.4
IRT Properties of Full Scale HOME

Information Function of the HOME Scale - All Items

PHD Study

Test information

Standard error
It probably affects the estimation of the technology of skill formation.

Why? Medium and high quality environments are difficult to separate.

It is possible that differences between medium and high quality environments are more (or less) important for child development than differences between medium and low quality environments.

Either case may lead to biases in the estimation of the technology of skill formation.
Monte Carlo Exercise

- Let \( h_1 \) denote human capital, \( \theta \) denote investments, and \( \zeta \) denote uncorrelated shocks. Consider the simple technology of skill formation:

\[
h_1 = 1.0 + 0.5\theta - 0.25\theta^2 + \zeta
\]  

(1)

- To obtain an idea about potential problems of using the HOME as a measure of investment to be used in the estimation of (1):
  - Generate a HOME Scale with desirable IRT properties as the “desired” HOME Scale;
  - Generate a HOME Scale that has “flawed” IRT properties as the “actual” HOME Scale;
  - Estimate \( \theta_{desired} \) from “desired” HOME Scale and \( \theta_{flawed} \) from “actual” HOME Scale;
  - Regress \( h_1 \) on quadratic function of \( \theta_{desired} \) and compare estimated with true coefficients;
  - Regress \( h_1 \) on quadratic function of \( \theta_{flawed} \) and compare estimated with true coefficients.
Monte Carlo Exercise

Coeff. on theta, Desired HOME

Kernel = epanechnikov, bandwidth = 0.0014

Coeff. on theta squared, Desired HOME

Kernel = epanechnikov, bandwidth = 0.0016

Coeff. on theta, Actual HOME

Kernel = epanechnikov, bandwidth = 0.0025

Coeff. on theta squared, Actual HOME

Kernel = epanechnikov, bandwidth = 0.0031
Measuring Quality and Quantity of Time: LENA Pro

![Graph showing language development over age for different groups of parents.](chart.png)

- **13 professional parents**
- **23 working-class parents**
- **6 welfare parents**

**Words addressed to the child**

**Age of child in months**
Measuring Quality and Quantity of Time: LENA Pro

1. Turn on the DLP and place it in the pocket of the child's LENA clothing.

2. After completing recording, plug the DLP into a PC running LENA Pro. The sophisticated language environment analysis software automatically uploads and processes the audio file.

3. The software generates the LENA reports and other analyses.

4. Export data from LENA Pro to mine your LENA data and perform custom in-depth analyses.
Figure 1. Human and LENA-based AWC estimates for 70 test files.
Measuring Quantity of Time: Meaningful Time
Philadelphia Human Development Study
Measuring Quality of Time: Conversation Turn Counts
Philadelphia Human Development Study
Measuring Quality and Quantity of Time: LENA Pro
Philadelphia Human Development Study

![Graph showing the relationship between variance and mean with data points labeled from 10 to 20.](Image)
This dependence between mean and variance (in hours when the mean is high, the variance is also high) is typical in count data.

One may think of taking the natural log of conversation turn counts and proceed with OLS-type analysis.

Not a good idea with count data:

- There are many zeros; taking the logs will eliminate the zeros from the analysis, which means it reduces cases of poor language environment.
- We want to identify households in terms of expected number of counts, not the expected log of number of counts (nonlinear transformation).
Let $Y_{i,j}$ denote the $j$th observation on conversation turn counts between an adult and child $i$.

Because these are counts, we model each observation as a Poisson random variable with parameter $\epsilon_i \lambda_{i,j}$ where $\epsilon_i$ is a random effect term and $\lambda_{i,j}$ is such that:

$$\ln \lambda_{i,j} = X_{i,j} \delta_j + \ln s_{i,j}$$

(2)

Vector $X_{i,j}$ contains variables that describe the context of measurement and $s_{i,j}$ is “exposure” (i.e., number of seconds that the LENA device was on during the $j$th measurement).
LENA Measurement in Practice

8:00 9:00 10:00 11:00 12:00 13:00 14:00 15:00 16:00 17:00 19:00 20:00 21:00 22:00

1 1 1 1 1 1 1 1 1 1 1

2 2 2 2 2 2 2 2 2 2 2

Child #1 Child #2
Daily Pattern of Talk for Typical Families
(Based on 2727 12-hour recordings)
Analysis of LENA Conversation Turn Counts Data

- Conditional on $\epsilon_i$, the probability of observing a count equal to:

$$
\Pr (y_{i,j} | \epsilon_i) = \frac{(\epsilon_i \lambda_{i,j})^{y_{i,j}}}{y_{i,j}!} e^{-\epsilon_i \lambda_{i,j}}
$$

where $\Pr (y_{i,j} | \epsilon_i) = \Pr (Y_{i,j} = y_{i,j} | \epsilon_i)$ is the probability that the count of variable $Y_{i,j}$ is equal to $y_{i,j}$ conditional on $\epsilon_i$.

- Assume that, conditional on $\epsilon_i$, the events are independent. Thus:

$$
\Pr (y_{i,1}, ..., y_{i,J} | \epsilon_i) = \left\{ \prod_{j=1}^{J} \left( \frac{(\lambda_{i,j})^{y_{i,j}}}{y_{i,j}!} \right) \right\} \epsilon_i^\sum_{j=1}^{J} y_{i,j} e^{-\epsilon_i \sum_{j=1}^{J} \lambda_{i,j}} \right\} \quad (3)
$$

- Because we don’t observe the random effect $\epsilon_i$, we need to integrate it out.

- We assume that $\epsilon_i$ has gamma distribution with mean one and variance $\frac{1}{\alpha}$.
Let $M_{i,j}$ denote the share of meaningful time of adult-child interaction in $j$th observation.

Because these are proportion data, we model each observation as the following logistic regression:

$$\ln \left\{ \frac{M_{i,j}}{1 - M_{i,j}} \right\} = X_{i,j}\rho_j + \mu_i + \nu_{i,j}$$

where $\mu_i$ is a random effect with mean zero and variance $\sigma_{\mu}^2$.

We are interested in estimating the unobserved heterogeneity captured by $\mu_i$ across families.
Quality and Quantity of Interaction by HOME
PHD Study

Quality of Interaction

Quantity of Interaction

- Low HOME Score
- Medium HOME Score
- High HOME Score
Flávio Cunha (Rice University)
Human Capital Formation in Childhood and Adolescence
August 7, 2017 136 / 186

The diagram shows the total number of adult words for different AWC levels:

- AWC >=80dB: 0% (6 words)
- AWC >=60dB: 51% (1,193 words)
- AWC >=50dB: 99% (2,317 words)
- AWC >=40dB: 100% (2,349 words)
Introducing Heterogeneity in Beliefs

Figure
Choice Set and Preferences

Red: Mother underestimates returns
Blue: Mother has unbiased returns
Why Heterogeneity in Beliefs?

- Time spent in activities that are appropriate for the child’s age (Kalil et al, 2012).
- Home visitation programs on parenting:
  - Nurse-Family Partnership (Olds et al, 2012).
  - HIPPY Program (Baker et al, 2002).
  - Parent as Teachers (PAT, Wagner et al, 1998)
  - Thirty Million Words Program (Suskind and Lefler, 2013).
  - Many others (Healthy Families, Healthy Start, CHIP of Virginia, MOM of Philadelphia, etc.)
My current research aims to answer the following questions:

- Can we measure parental beliefs about the technology of skill formation?
- If so:
  - How do parental beliefs compare with objective estimates of the technology of skill formation?
  - Is there heterogeneity in parental beliefs?
- If so, does the heterogeneity in beliefs predict heterogeneity in investments?
- If so, can we change parental investments by affecting parental beliefs?
The technology of skill formation is:

\[
\ln h_{i,1} = \psi_0 + \psi_1 \ln h_{0,i} + \psi_2 \ln x_i + \psi_3 \ln h_{0,i} \ln X_i + \nu_i
\]
Let $\Psi_i$ denote the mother’s information set.

Let $E(\psi_j | h_{0,i}, x_i, \Psi_i) = \mu_{i,j}$ and assume that $E(\nu_i | \Psi_i) = 0$.

From the point of view of the mother:

$$E(\ln h_{i,1} | h_{0,i}, x_i, \Psi_i) = \mu_{i,0} + \mu_{i,1} \ln h_{0,i} + \mu_{i,2} \ln x_i + \mu_{i,3} \ln h_{0,i} \ln x_i$$
Consider a simple static model. Parent’s utility is:

\[ u(c_i, h_{i,1}; \alpha_{i,1}, \alpha_{i,2}) = \ln c_i + \alpha_{i,1} \ln h_{i,1} + \alpha_{i,2} \ln x_i \]

Budget constraint is:

\[ c_i + px_i = y_i. \]
The problem of the mother is to maximize expected utility subject to the mother’s information set, the budget constraint, and the technology of skill formation.

The solution is

\[ x_i = \left[ \frac{\alpha_{i,1} \left( \mu_{i,2} + \mu_{i,3} \ln h_{0,i} \right) + \alpha_{i,2}}{1 + \alpha_{i,1} \left( \mu_{i,2} + \mu_{i,3} \ln h_{0,i} \right) + \alpha_{i,2}} \right] \frac{y_i}{p} \]

Clearly, we cannot separately identify \( \alpha_{i} \) from \( \mu_{i,\gamma} \) if we only observe \( x_i, y_i, \) and \( p. \)
Identification

- Elicit maternal beliefs.
- Elicit maternal preferences.
- Estimate the technology of skill formation.
Eliciting beliefs: Steps

- Measure actual child development: MSD and Item Response Theory (IRT).
- Develop the survey instrument to elicit beliefs $E[\ln h_{i,1}|h_0,x,\psi_i]$: 
  - Reword MSD items.
  - Create hypothetical scenarios of $h_0$ and $x$.
- Estimate beliefs from answers allowing for error in responses.
## SECTION 3: MOTOR AND SOCIAL DEVELOPMENT

### PART H: (22 MONTHS - 3 YEARS, 11 MONTHS)

**MOTHER/GUARDIAN:**

If ____________________________ is **at least 22 months** old, but **not yet 4 years** old, please answer these 15 questions.

<table>
<thead>
<tr>
<th>Question</th>
<th>Yes</th>
<th>No</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Has your child ever let someone know, without crying, that wearing wet (soiled) pants or diapers bothered him/her?</td>
<td>1</td>
<td>0</td>
<td>72/</td>
</tr>
<tr>
<td>2. Has your child ever spoken a partial sentence of 3 words or more?</td>
<td>1</td>
<td>0</td>
<td>73/</td>
</tr>
<tr>
<td>3. Has your child ever walked upstairs by himself/herself without holding on to a rail?</td>
<td>1</td>
<td>0</td>
<td>74/</td>
</tr>
<tr>
<td>4. Has your child ever washed and dried his/her hands without any help except for turning the water on and off?</td>
<td>1</td>
<td>0</td>
<td>75/</td>
</tr>
<tr>
<td>5. Has your child ever counted 3 objects correctly?</td>
<td>1</td>
<td>0</td>
<td>76/</td>
</tr>
</tbody>
</table>
Eliciting beliefs: Item response theory

Let $d_{i,j}^* = b_{0,j} + b_{1,j} \left( \ln a_i + \frac{b_{2,j}}{b_{1,j}} \theta_i \right) + \eta_{i,j}$

We observe $d_{i,j} = 1$ if $d_{i,j}^* \geq 0$ and $d_{i,j} = 0$, otherwise.

Measure of (log of) human capital: $\ln h_i = \ln a_i + \frac{b_{2,j}}{b_{1,j}} \theta_i$.

In this sense, $\theta_i$ is deviation from typical development for age.
Figure 4
Probability as a Function of Child's Age

- **Speak partial sentence, data**
- **Speak partial sentence, predicted**
In order to measure $E [ \ln h_{i,1} | h_0, x, \psi_i ]$, we take the tasks from the MSD Scale, but instead of asking: “Has your child ever spoken a partial sentence with three words or more?”, we ask:

- **Method 1**: How likely is it that a baby will speak a partial sentence with three words or more by age 24 months?
- **Method 2**: What is the youngest and oldest age a baby learns to speak a partial sentence with three words or more?
Eliciting beliefs: Scenarios of human capital and investments

- We consider four scenarios:
  - Scenario 1: Child is healthy at birth (e.g., normal gestation, birth weight, and birth length) and investment is high (e.g., six hours per day).
  - Scenario 2: Child is healthy at birth and investment is low (e.g., two hours per day).
  - Scenario 3: Child is not healthy at birth (e.g., premature, low birth weight, and small at birth) and investment is high.
  - Scenario 4: Child is not healthy at birth and investment is low.

- Scenarios are described to survey respondents through a video.
**Method 1: Transforming probabilities into mean beliefs**

- **Method 1:** How likely is it that a baby will speak a partial sentence with three words or more by age 24 months?
- Let’s say that when investment is high – that is, when $x = \bar{x}$ – the mother states that there is a 75% chance that the child will learn how to speak a partial sentence with three words or more.
- And when investment is low – that is, when $x = \underline{x}$ – the mother states that there is a 25% chance that the child will learn how to speak a partial sentence with three words or more.
- We convert this probability statement into an age-equivalent statement using the NHANES data.
Method 2: Transforming age ranges into probabilities

- **Method 2:** What is the youngest and oldest age a baby learns to speak a partial sentence with three words or more?
- Let’s say that when investment is high, so that $x = \bar{x}$, the mother states that the youngest and oldest ages a baby will learn how to speak a sentence with three words or more are, respectively, 18 and 28 months.
- And when investment is low, so that $x = \underline{x}$, the mother states that the ages are 20 and 30 months.
- We need to transform the age ranges into probabilities. We use the age ranges to estimate a mother-specific IRT model.
Figure 3
Transforming age range into probability

Age (in months)

Probability

High investment
Figure 3
Transforming age range into probability

Logistic prediction, high
High investment
Figure 3
Transforming age range into probability

- Logistic prediction, high
- High investment
Figure 3

Transforming age range into probability

- Logistic prediction, high
- Logistic prediction, low
- High investment
- Low investment
Figure 3
Transforming age range into probability

- Logistic prediction, high
- Logistic prediction, low
- High investment
- Low investment
Method 2: Transforming probabilities into mean beliefs

- Method 2: Given scenario for $h_0$ and $x$, how likely is it that a baby will speak a partial sentence with three words or more by age 24 months?
- Given maternal supplied age range and the logistic assumption, we conclude that when $x = \bar{x}$, the mother believes that there is a 75% chance that the child will learn how to speak a partial sentence with three words or more.
- Analogously, when $x = x$, the mother believes that there is a 25% chance that the child will learn how to speak a partial sentence with three words or more.
- We convert this probability statement into an age-equivalent statement using the NHANES data.
Figure 3

Expected development for two levels of investments ($x$)

**Age range to probability**
Speak partial sentence - MKIDS

**Probability to expected development**
Speak partial sentence - NHANES

Data Predicted

Expected development for two levels of investments ($x$)
Recovering mean beliefs: Measurement error model

- Let $\ln q^L_{i,j,k}$ denote an error-ridden measure of $E \left[ \ln h_{i,1} \mid h_{0,k}, x_k, \psi_i \right]$ generated by “how likely” questions:
  $$\ln q^L_{i,j,k} = E \left[ \ln h_{i,1} \mid h_{0,k}, x_k, \psi_i \right] + \epsilon^L_{i,j,k}.$$  

- Let $\ln q^A_{i,j,k}$ denote an error-ridden measure of $E \left[ \ln h_{i,1} \mid h_{0,k}, x_k, \psi_i \right]$ generated by “age range” questions:
  $$\ln q^A_{i,j,k} = E \left[ \ln h_{i,1} \mid h_{0,k}, x_k, \psi_i \right] + \epsilon^A_{i,j,k}.$$  

- For each scenario, we have multiple measures of the same underlying latent variable.
Recovering mean beliefs:

- Use technology of skill formation, and the mother’s information set, to obtain:

\[
\ln q_{i,j,k}^L = \mu_{i,0} + \mu_{i,1} \ln h_{0,k} + \mu_{i,2} \ln x_k + \mu_{i,3} \ln h_{0,k} \ln x_k + \epsilon_{i,j,k}^L.
\]

\[
\ln q_{i,j,k}^A = \mu_{i,0} + \mu_{i,1} \ln h_{0,k} + \mu_{i,2} \ln x_k + \mu_{i,3} \ln h_{0,k} \ln x_k + \epsilon_{i,j,k}^A.
\]

- We have a factor model where:
  - \( \mu_i = (\mu_{i,0}, \mu_{i,1}, \mu_{i,2}, \mu_{i,3}) \) are the latent factors;
  - \( \lambda_k = (1, h_{0,k}, \ln x_k, \ln h_{0,k} \ln x_k) \) are the factor loadings;
  - \( \epsilon_{i,j,k} = (\epsilon_{i,j,k}^L, \epsilon_{i,j,k}^A) \) are the uniquenesses.
Eliciting beliefs: Intuitive explanation

- Let $E [\ln h_{i,1} | h_0, h, \Psi_i]$ denote maternal expectation of child development at age 24 months conditional on the child’s initial level of human capital, investments, and the mother’s information set.

- Assume, for now, technology is Cobb-Douglas.

- Suppose we measure $E [\ln h_{i,1} | h_0, x, \Psi_i]$ at two different levels of investments:

  $$E [\ln h_{i,1} | h_0, \bar{x}, \Psi_i] = \mu_{i,0} + \mu_{i,1} \ln h_0 + \mu_{i,2} \ln \bar{x}$$

  $$E [\ln h_{i,1} | h_0, x, \Psi_i] = \mu_{i,0} + \mu_{i,1} \ln h_0 + \mu_{i,2} \ln x$$

- Subtracting and re-organizing terms:

  $$\mu_{i,2} = \frac{E [\ln h_{i,1} | h_0, \bar{x}, \Psi_i] - E [\ln h_{i,1} | h_0, x, \Psi_i]}{\ln \bar{x} - \ln x}$$
Important issue

- We could use only one MSD item to elicit beliefs.
- But, if we use more items, we can relax assumptions about measurement error.
- And, we can check for consistency in answers.
Figure 5
Comparing answers across scenarios

Age range into probability

Speaks partial sentence
Knows own age and sex

Probability into expected development

Speaks partial sentence
Knows own age and sex
Estimation of Preferences

- The investment policy function is:

\[ x_i = \left[ \frac{\alpha_{i,1} (\mu_{i,2} + \mu_{i,3} \ln h_{0,i}) + \alpha_{i,2}}{1 + \alpha_{i,1} (\mu_{i,2} + \mu_{i,3} \ln h_{0,i}) + \alpha_{i,2}} \right] \frac{y_i}{p} \]

where \( \alpha_{i,1} \) and \( \alpha_{i,2} \) captures heterogeneity in preferences.

- The usual procedure is to work with observed investment data.

- We are in the field collecting these investment data.
Today, we elicit the preference parameters by stated-choice data (as it is commonly applied in Marketing).

We tell the respondent to assume that the child’s initial level of human capital is high.

Then, we create nine hypothetical scenarios of monthly income and prices:

<table>
<thead>
<tr>
<th>Income</th>
<th>Price</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
<th>Scenario 4</th>
<th>Scenario 5</th>
<th>Scenario 6</th>
<th>Scenario 7</th>
<th>Scenario 8</th>
<th>Scenario 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1500</td>
<td>$30</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$2000</td>
<td>$45</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$2500</td>
<td>$60</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Estimation of Preferences

In order to link investment to time, we prepared a three-minute video in which we explain to the respondent that the more time that the mother interacts with the child, the more money she has to spend every month buying educational goods such as child books and educational toys.

Our goal is to pass on to the respondent the idea that investment is costly.

Respondents are not familiar with the concept of “opportunity cost.”
For each combination of prices and income, we ask the respondents the following question: Suppose that your household income is $y$ per month and that for each hour per day that the mother spends interacting with the child she has to spend $p$ per month on educational goods. Consider the following four options:

The four options correspond to two, three, four, and five hours of investments per day.

Thus, if the respondent reports $x_{i,m,n}$ hours of investment per day when price is $p_m$ and income is $y_n$, then share of income allocated to investments, $s_{m,n}$ is:

$$s_{i,m,n} = \frac{p_m x_{i,m,n}}{y_n}$$
Note that the ratio, \( r_{i,m,n} \) is:

\[
r_{i,m,n} = \frac{s_{i,m,n}}{1 - s_{i,m,n}} = \alpha_{i,1} (\mu_{i,2} + \mu_{i,3} \ln h_{0,i}) + \alpha_{i,2} + \xi_{i,m,n}
\]

The parameters \( \alpha_{i,1} \) and \( \alpha_{i,2} \) can be estimated as a simple random-effects model.
Descriptive Information about Participants: MKIDS and PHD

Pilot Study: Maternal Knowledge of Infant Development Study (MKIDS)

- 777 participants, all African-American.
- MKIDS: 60% are primiparous; PHD: 100% are primiparous.
- 80% are single (not cohabiting or married).
- 80% are at most 25 years-old.
- Median household income is below the second decile of U.S. distribution.
- Low education sample: only 12% of respondents have a two-year college degree or more.
<table>
<thead>
<tr>
<th>Type of Elicitation Method</th>
<th>MKIDS</th>
<th>PHD</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Only probability</td>
<td>20</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>Only age ranges</td>
<td>233</td>
<td>0</td>
<td>233</td>
</tr>
<tr>
<td>Both methods</td>
<td>70</td>
<td>454</td>
<td>524</td>
</tr>
</tbody>
</table>

### MSD Items

<table>
<thead>
<tr>
<th>MSD Items</th>
<th>MKIDS</th>
<th>PHD</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wearing wet pants bothers child</td>
<td>323</td>
<td>0</td>
<td>323</td>
</tr>
<tr>
<td>Speak partial sentence</td>
<td>323</td>
<td>454</td>
<td>777</td>
</tr>
<tr>
<td>Say first and last name</td>
<td>323</td>
<td>454</td>
<td>777</td>
</tr>
<tr>
<td>Count 3 objects correctly</td>
<td>323</td>
<td>454</td>
<td>777</td>
</tr>
<tr>
<td>Know own age and sex</td>
<td>323</td>
<td>454</td>
<td>777</td>
</tr>
<tr>
<td>Says the names of 4 colors</td>
<td>323</td>
<td>0</td>
<td>323</td>
</tr>
<tr>
<td>Count out loud up to 10</td>
<td>323</td>
<td>0</td>
<td>323</td>
</tr>
<tr>
<td>Draw picture of man/woman</td>
<td>323</td>
<td>0</td>
<td>323</td>
</tr>
</tbody>
</table>

### Hypothetical scenarios

<table>
<thead>
<tr>
<th>Hypothetical scenarios</th>
<th>MKIDS</th>
<th>PHD</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>158</td>
<td>454</td>
<td>612</td>
</tr>
<tr>
<td>Alternative scenario #1</td>
<td>42</td>
<td>0</td>
<td>42</td>
</tr>
<tr>
<td>Alternative scenario #2</td>
<td>91</td>
<td>0</td>
<td>91</td>
</tr>
<tr>
<td>Alternative scenario #3</td>
<td>32</td>
<td>0</td>
<td>32</td>
</tr>
</tbody>
</table>

### Stated choice data

<table>
<thead>
<tr>
<th>Stated choice data</th>
<th>MKIDS</th>
<th>PHD</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypothetical scenarios for prices of investment and income</td>
<td>158</td>
<td>0</td>
<td>158</td>
</tr>
<tr>
<td>Rank</td>
<td>Item Description</td>
<td>Obs.</td>
<td>NHANES</td>
</tr>
<tr>
<td>------</td>
<td>----------------------------------------------------------------------------------</td>
<td>------</td>
<td>--------</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Chils lets someone know that wearing wet pants bothers him/her?</td>
<td>90</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Child speaks a partial sentence of 3 words or more</td>
<td>544</td>
<td>0.72</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Child counts 3 objects correctly?</td>
<td>544</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Child knows own age and sex</td>
<td>544</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Child says first and last name together without someone's help</td>
<td>544</td>
<td>0.26</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Child says the names of at least 4 colors</td>
<td>90</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Child counts out loud up to 10?</td>
<td>90</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Child draws a picture of a man/woman, 2 parts besides head</td>
<td>90</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Note: Standard errors in parenthesis.
Table 3
Maternal Beliefs about the Technology of Skill Formation

<table>
<thead>
<tr>
<th></th>
<th>25th percentile</th>
<th>Median</th>
<th>75th percentile</th>
<th>Mean</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_{\psi,0}$</td>
<td>-0.015</td>
<td>0.101</td>
<td>0.236</td>
<td>0.115</td>
<td>0.035</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.007)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>$\mu_{\psi,1}$</td>
<td>0.077</td>
<td>0.296</td>
<td>0.554</td>
<td>0.365</td>
<td>0.204</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.016)</td>
<td>(0.022)</td>
<td>(0.016)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>$\mu_{\psi,2}$</td>
<td>0.065</td>
<td>0.166</td>
<td>0.285</td>
<td>0.192</td>
<td>0.046</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.010)</td>
<td>(0.008)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>$\mu_{\psi,3}$</td>
<td>-0.008</td>
<td>0.094</td>
<td>0.335</td>
<td>0.190</td>
<td>0.320</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.010)</td>
<td>(0.024)</td>
<td>(0.020)</td>
<td>(0.051)</td>
</tr>
</tbody>
</table>

Note: Standard errors in parenthesis.
Sensitivity analysis

Table 4
Alternative Definition of Scenarios and Maternal Beliefs

<table>
<thead>
<tr>
<th>Regressors</th>
<th>$\mu_{\psi,0}$</th>
<th>$\mu_{\psi,1}$</th>
<th>$\mu_{\psi,2}$</th>
<th>$\mu_{\psi,3}$</th>
<th>(p-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept (baseline)</td>
<td>0.018</td>
<td>0.147</td>
<td>0.112</td>
<td>0.070</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.043)</td>
<td>(0.022)</td>
<td>(0.062)</td>
<td>-</td>
</tr>
<tr>
<td>Dummy for alternative scenario #1</td>
<td>0.067</td>
<td>-0.027</td>
<td>-0.032</td>
<td>-0.081</td>
<td>1.080</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.094)</td>
<td>(0.048)</td>
<td>(0.136)</td>
<td>(0.364)</td>
</tr>
<tr>
<td>Dummy for alternative scenario #2</td>
<td>0.280</td>
<td>0.469</td>
<td>0.175</td>
<td>0.424</td>
<td>33.910</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.071)</td>
<td>(0.037)</td>
<td>(0.103)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Dummy for alternative scenario #3</td>
<td>0.206</td>
<td>0.027</td>
<td>0.051</td>
<td>0.091</td>
<td>6.750</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.104)</td>
<td>(0.054)</td>
<td>(0.152)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

Note: Standard errors in parenthesis, except in the F-test column where we report p-values.
Figure 9

Demand curves

Engel curves

- Income = $1500
- Income = $2000
- Income = $2500

- Price = $30
- Price = $45
- Price = $45

- Income = $1500
- Income = $2000
- Income = $2500
### Table 5
Maternal Beliefs about the Technology of Skill Formation

<table>
<thead>
<tr>
<th></th>
<th>25th percentile</th>
<th>Median</th>
<th>75th percentile</th>
<th>Mean</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_{i,1}$</td>
<td>0.0261</td>
<td>0.0312</td>
<td>0.0400</td>
<td>0.0313</td>
<td>0.0002</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0002)</td>
<td>(0.0007)</td>
<td>(0.0004)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>$\alpha_{i,2}$</td>
<td>0.0669</td>
<td>0.0777</td>
<td>0.0942</td>
<td>0.0795</td>
<td>0.0003</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
<td>(0.0008)</td>
<td>(0.0007)</td>
<td>(0.0005)</td>
<td>(0.0000)</td>
</tr>
</tbody>
</table>

Note: Standard errors in parenthesis.
### Table 7

**Comparative Statics of Investments**

<table>
<thead>
<tr>
<th></th>
<th>Median</th>
<th>75th percentile</th>
<th>% Change in investments</th>
<th>% Change in parameter</th>
<th>Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_1$</td>
<td>1.70</td>
<td>1.73</td>
<td>1.6%</td>
<td>28.0%</td>
<td>5.8%</td>
</tr>
<tr>
<td>$\alpha_2$</td>
<td>1.70</td>
<td>2.01</td>
<td>18.3%</td>
<td>21.4%</td>
<td>85.2%</td>
</tr>
<tr>
<td>$\mu_{\psi,2}$</td>
<td>1.70</td>
<td>1.77</td>
<td>4.1%</td>
<td>72.0%</td>
<td>5.8%</td>
</tr>
<tr>
<td>$\mu_{\psi,3}$</td>
<td>1.70</td>
<td>1.70</td>
<td>0.2%</td>
<td>257.1%</td>
<td>0.1%</td>
</tr>
<tr>
<td>$\mu_{\psi,3}$</td>
<td>1.70</td>
<td>1.86</td>
<td>9.3%</td>
<td>257.1%</td>
<td>3.6%</td>
</tr>
</tbody>
</table>

This table shows the comparative statics of optimal investments in relation to preference and belief parameters. Each row shows what happens to investments as we move one parameter and fix the other parameters at the median value. In the last row, we replace the human capital at birth from the mean value to the value at the first percentile.
<table>
<thead>
<tr>
<th>Cases</th>
<th>Factual Investment</th>
<th>Counterfactual Investment</th>
<th>% Change</th>
<th>Effect size</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_{\psi,2} = 0.267$</td>
<td>1.84</td>
<td>1.92</td>
<td>4.4%</td>
<td>10.3%</td>
</tr>
<tr>
<td>$\mu_{\psi,3} = 0.000$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\mu_{\psi,2} = 0.454$</td>
<td>1.84</td>
<td>2.05</td>
<td>11.7%</td>
<td>26.9%</td>
</tr>
<tr>
<td>$\mu_{\psi,3} = 0.000$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Beliefs and Investments: Anthropology

- !Kung San in the Kalahari desert in Botswana and Namibia (e.g., Lee, 1979) vs. Ache in Paraguay (see Kaplan and Dove, 1987; Hill and Hurtado, 1996).
  - Both groups believe that the development of motor skills by children depends on parental encouragement and teaching.
  - Different environments lead both groups to behave in very different ways.
- Gusii in Kenya (see LeVine et al, 1994).
The argument that low subjective expectations about returns may affect investments has been recognized in developmental psychology for over 50 years (Hunt, 1961; Vygostky, 1978).

Huge empirical literature attempting to estimate what parents know about child developmental milestones (Epstein, 1979; Hess et al., 1980; Ninio, 1988; Mansbach and Greenbaum, 1999).
Expecting too little, too late however is not characteristic of teenagers’ knowledge in all areas of development. In fact, when we look at items about basic care, health and nutrition, and perceptual and motor development, we discover that their expectations are quite accurate. By contrast, when we look at how they view infant needs and abilities in the areas of mental development – cognitive, social, and language, it is here that we find teenagers attributing skills to babies many months too late. And, not surprisingly, our analyses show that it is the younger infant who is most likely viewed as a creature of physical needs and growth without corresponding mental activity.

This view of the infant is also evident in teenagers’ responses to the videotape measure. Mean ratings indicate that they can neither observe the signs of learning in babies nor recognize the appropriate activities by which adults support this learning.
Lynd and Lynd (1929, 1937) reported that working-class mothers ranked “strict obedience” as their most important childrearing goal more frequently than higher-SES mothers did. Many studies, conducted in the US in the 1990s or in other developed countries, replicate these findings.

Kohn (1963) argues that the stronger preferences towards socio-emotional skills by lower-SES mothers reflect those mothers’ forecasts for their children choosing occupations in which obedience and conformity have relatively higher returns.

This finding is also reported in Lareau’s ethnographic study *Unequal Childhood*: “Natural Accomplishment of Growth” and “Concerted Cultivation.”
Aizer and Stroud (2010) track the smoking habits of educated and non-educated pregnant women before and after the release of the 1964 Surgeon General Report on Smoking and Health.

Before the release of the report, educated and non-educated pregnant women smoked at roughly the same rates.

After the report, the smoking habits of educated women decreased immediately, and there was suddenly a ten-percentage point gap between pregnant women who were educated and non-educated in smoking.

Could the divergence of early investments in the last 20 years be the result of divergence in expectations? We don’t know, but it is possible that this is the case.
Discussion

- I presented research in which we aim to formulate a model of human development in which mothers have subjective expectations about a parameter of the technology of skill formation.

- The model is useful to understand how maternal knowledge about the importance of investments in children affect investment choices.

- Large body of literature in many fields suggest that beliefs may play an important role in determining familial investments in children.
Discussion

- At the same time, the literature suggests that these beliefs are endogenous.
- Parents expectations about future occupations of children, or the skills that will be most important for their survival, determine parental beliefs about what skills children should learn, and what skills they believe are malleable.
- So, if correct, this framework suggests that it may be difficult to change parental beliefs.
- At the same time, research in economics shows that most educated parents react to information that improves children’s health.
- And some home visitation programs have been very successful in positively affecting children’s health (but not all).
- So, future research should aim to understand the process of belief formation.