Interventions: Treatment Effects and Mechanisms Producing Treatment Effects
Part IVA

James J. Heckman
University of Chicago

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Using Economics to Go Behind Estimated Program Treatment Effects and Beyond Meta-Analyses of Treatment Effects: Linking the Program Evaluation Literature with the Economics of the Family

- Widely used “metanalyses” of early childhood programs do not recognize that the various interventions in early childhood previously implemented differ in substantial ways.

  1. The populations targeted differ.
  2. The objectives and curricula of the programs differ.
  3. The measurement systems for backgrounds and outcomes differ among each other and also with observational studies.
  4. The methods of evaluation differ.

- Need to integrate the studies of family influence with the intervention studies to understand how interventions affect family life.

- Need to compare alternative policies in comparable metrics; i.e., rates of return to policies or cost-benefit analyses.
Today I focus on the evidence regarding interventions which have a long-term follow-up, which have been extensively studied or widely adopted, or that offer unique insights.

We draw on the analysis of Kautz et al. (2014) and Elango et al. (2016) where a more comprehensive discussion of each program is presented.
Fostering and Measuring Skills: Improving Cognitive and Noncognitive Skills to Promote Lifetime Success
OECD, 2014

http://tinyurl.com/lqnvb6w
Sneha Elango, Andrés Hojman, Jorge Luis García, and James J. Heckman

**Early Childhood Education**

The Main Findings of the Literature on Skill Interventions over the Life Cycle
Three striking patterns emerge.

First, many early childhood interventions have longer follow-ups (10 or 20 years) than do adolescent interventions.

Second, evaluations of early childhood programs tend to measure cognitive and noncognitive skills in addition to a variety of later-life outcomes.
Many evaluations of programs for adolescents focus solely on labor market outcomes.

Examination of the curriculum of these programs is necessary to understand their primary program focus (e.g., cognitive or noncognitive stimulation).

Third, the selection of children into early interventions is often dependent on parental choices, whereas adolescents participants decide themselves whether to opt in.
Three main findings emerge.

First, only very early interventions (before age 3) improve IQ in lasting ways consistent with the evidence that early childhood is a critical period for cognitive development.

Second, programs targeting disadvantaged adolescents less effective than are early intervention programs.

This evidence is broadly consistent with dynamic complementarity.

Many successful adolescent programs are consequences of the direct effect of incentives put in place by these programs (versions of incapacitation effects), but they fail to have lasting effects.
Parenting Is a Main Mechanism Through which the Programs Have an Effect

- Third, the most promising adolescent interventions feature mentoring and scaffolding.
- They often integrate work with traditional education and attenuate the rigid separation between school and work that characterizes the American high school.
- Mentoring involves teaching valuable character (noncognitive) skills (showing up for work, cooperating with others, and persevering on tasks).
• The effectiveness of mentoring programs is consistent with the evidence on the importance of attachment, parenting, and interaction discussed below.

• **Some form of mentoring and parenting is present in all successful intervention programs at all stages of childhood.**
Long-Term Follow-Ups Are Vital

- Many programs have short-term effects but no long-term effects.
- Others have no short-term effects (for some measures) but long-term effects.
Non-Cognitive Skills Are Important Channels of Childhood Benefits Throughout Early Childhood and Adolescence

- Only interventions that started before age 3 had a long-term effect on IQ
- Many interventions starting after age 3 have effectively improved outcomes by improving non-cognitive skills
- Adolescent interventions that teach personality skills in the workplace (or specific context) are promising
Table 1: Summary of Effects for Main Interventions

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<tr>
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<th>Age</th>
<th>Duration</th>
<th>Target</th>
<th>Selection</th>
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Heckman Interventions
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</table>
Perry Preschool Program
• The Perry Preschool program targeted 3- and 4-year old low income black children with initial IQ below 85 at age 3.
• Selection into the program was based on random assignment.
• Children attended 2.5 hours of center-based preschool five days a week for two years.
• Teachers were also involved in home visits during which they interacted, played and talked with the child.
• Implemented years: 1962–1967
• 5 cohorts of 3–4 year-olds; 123 participants
• Treatment lasted 1–2 years and included center-based care and home visits & parenting instruction
• The program focused on building organizational and social skills and was designed to cultivate independence and a sense of responsibility in the children (Schweinhart et al., 1993).

• The daily routing was understood as a key component of teaching children temporal relations (Weikart et al., 1971).
• Children first planned an activity to execute and then would go to the art, large motor, doll or quiet center to complete their planned activity.

• The program ended after two years of enrollment and then children from both treatment and control group attended the same school.
No IQ Effects
Figure 1: Perry Preschool Program: IQ, by age and treatment group

IQ

Entry 4 5 6 7 8 9 10

Age

Treatment Group
Control Group

Source: Perry Preschool Program. IQ measured on the Stanford Binet Intelligence Scale (Terman & Merrill, 1960). Test was administered at program entry and each of the ages indicated.
• Has a statistically significant rate of return of around 7–10% per annum – for both boys and girls – above the post-World War II stock market returns to equity in U.S. labor market, estimated to be 5.8%.

• The Perry Preschool Program worked primarily through **non-cognitive** channels.
Figure 2: Mechanisms: Externalizing Behavior, Males

(a) Control

(b) Treatment

*Data:* Perry Preschool Program.

*Source:* Heckman, Pinto, Savelyev (2013).
Figure 3: Perry Preschool Program: Histograms of Indices of Personality Skills and CAT Scores

Panel A. Externalizing behavior, control

Panel B. Externalizing behavior, treatment

Source: Heckman et al. (2013).
Figure 3: Perry Preschool Program: Histograms of Indices of Personality Skills and CAT Scores, Cont’d

Panel C. Academic motivation, control

Panel D. Academic motivation, treatment

Source: Heckman et al. (2013).
Figure 3: Perry Preschool Program: Histograms of Indices of Personality Skills and CAT Scores, Cont’d

Panel E. CAT total at age 14, control

Panel F. CAT total at age 14, treatment

Source: Heckman et al. (2013).
### Table 2: Perry Preschool Program: Program Treatment Effects

<table>
<thead>
<tr>
<th>Variable</th>
<th>Treatment effect</th>
<th>Control group</th>
<th>Treatment group</th>
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<tbody>
<tr>
<td></td>
<td>Effect</td>
<td>Effect size</td>
<td>p-value</td>
</tr>
<tr>
<td><strong>Panel A. Males</strong></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>CAT total at age 14, end of grade 8</td>
<td>0.566*</td>
<td>0.652</td>
<td>(0.060)</td>
</tr>
<tr>
<td>Number of misdemeanor arrests, age 27</td>
<td>−1.21**</td>
<td>−0.363</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Number of felony arrests, age 27</td>
<td>−1.12</td>
<td>−0.324</td>
<td>(0.101)</td>
</tr>
<tr>
<td>Number of adult arrests (misd.+fel.), age 27</td>
<td>−2.33**</td>
<td>−0.402</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Monthly income, age 27</td>
<td>0.876**</td>
<td>0.607</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Use tobacco, age 27</td>
<td>−0.119*</td>
<td>−0.236</td>
<td>(0.093)</td>
</tr>
<tr>
<td>Number of misdemeanor arrests, age 40</td>
<td>−3.13**</td>
<td>−0.372</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Number of felony arrests, age 40</td>
<td>−1.14*</td>
<td>−0.266</td>
<td>(0.092)</td>
</tr>
<tr>
<td>Number of adult arrests (misd.+fel.), age 40</td>
<td>−4.26**</td>
<td>−0.373</td>
<td>(0.041)</td>
</tr>
<tr>
<td>Number of lifetime arrests, age 40</td>
<td>−4.20*</td>
<td>−0.346</td>
<td>(0.053)</td>
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<tr>
<td>Employed, age 40</td>
<td>0.200**</td>
<td>0.394</td>
<td>(0.024)</td>
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<tr>
<td>Sample size</td>
<td>72</td>
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### Table 2: Perry Preschool Program: Program Treatment Effects, Cont’d

<table>
<thead>
<tr>
<th>Variable</th>
<th>Treatment effect</th>
<th>Control group</th>
<th>Treatment group</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Effect</td>
<td>Effect size</td>
<td>p-value</td>
</tr>
<tr>
<td><strong>Panel B. Females</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAT total, age 8</td>
<td>0.565*</td>
<td>0.614</td>
<td>(0.062)</td>
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<tr>
<td>CAT total, age 14</td>
<td>0.806**</td>
<td>0.909</td>
<td>(0.014)</td>
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<tr>
<td>Any special education, age 14</td>
<td>−0.262**</td>
<td>−0.514</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Mentally impaired at least once, age 19</td>
<td>−0.280**</td>
<td>−0.569</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Number of misdemeanor violent crimes, age 27</td>
<td>−0.423**</td>
<td>−0.292</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Number of felony arrests, age 27</td>
<td>−0.269**</td>
<td>−0.325</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Jobless for more than 1 year, age 27</td>
<td>−0.292*</td>
<td>−0.573</td>
<td>(0.071)</td>
</tr>
<tr>
<td>Ever tried drugs other than alcohol or weed, age 27</td>
<td>−0.227**</td>
<td>−0.530</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Number of misdemeanor violent crimes, age 40</td>
<td>−0.537**</td>
<td>−0.364</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Number of felony arrests, age 40</td>
<td>−0.383**</td>
<td>−0.425</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Number of lifetime violent crimes, age 40</td>
<td>−0.574**</td>
<td>−0.384</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Months in all marriages, age 40</td>
<td>39.6*</td>
<td>0.539</td>
<td>(0.076)</td>
</tr>
<tr>
<td>Sample size</td>
<td>51</td>
<td>26</td>
<td></td>
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</table>
The mediating effects of externalizing behavior are not only statistically significant, but also economically significant. Reported arrests and registered crimes are only a small fraction of the actual number of crimes. For instance, only one in 15 property crimes and one in five violent crimes actually leads to an arrest. We find that experimentally induced reductions in externalizing behavior (by one standard deviation) lead to a decline in the total number of lifetime arrests by statistically significant 1.7 (p = 0.077) and the number of felony arrests by 0.6 (p = 0.056) for males at age 40. For females, the total number of felony arrests by age 40 is reduced by 0.31 (p = 0.050), and the number of registered lifetime violent crimes is reduced by 0.65 (p = 0.046).  

**Source:** Heckman et al. (2013).
is likely several times larger than these reductions in the number of arrests and registered crimes. Since externalizing behavior is both malleable at early ages (see Figure 5) and strongly predictive of crime (see Table 3), it should not be surprising that crime reduction has been found to be a major benefit of the Perry program.

We also decompose the effect of the program on an achievement test (CAT) for both males and females. For females, enhancements in academic motivation explain about 30 percent of the treatment effect on CAT scores at age eight. This estimate is statistically significant at a 10 percent level ($p = 0.057$). For CAT scores at age 14, the role of academic motivation is not precisely determined for males or for females ($p = 0.161$ and 0.528).

Finally, we decompose a number of education, labor market, and health outcomes. Academic motivation consistently explains a share of treatment effects for all education-related outcomes, which is not surprising given strong links between academic motivation and education outcomes presented in Table 3. However, only some components of these decompositions are precisely determined (e.g., CAT and the status of being mentally impaired for females).

For labor market outcomes, we find that about 20 percent of the treatment effect on monthly income at age 27 ($p = 0.089$) and also about 20 percent of the treatment effect on the probability of employment at age 40 ($p = 0.085$) are explained by early improvements in externalizing behavior. Additionally, externalizing behavior explains about 40 percent of tobacco use at age 27 ($p = 0.046$).

**Source:** Heckman et al. (2013).
Figure 6: Felt as belonging to school at 19 (sign of factor); feels able to change things in life at 40; has little control over things at 40

Average Treatment Effect, Pooled: .48 (p-value: .01)
Average Treatment Effect, Females: .5600000000000001 (p-value: .03)
Average Treatment Effect, Males: .4 (p-value: .06)
**Figure 7:** Drugs or alcohol at age 15 (sign of factor); guns or knifes at 15

Average Treatment Effect, Pooled: −.3 (p-value: .07)
Average Treatment Effect, Females: −.46 (p-value: .09)
Average Treatment Effect, Males: −.19 (p-value: .22)
Figure 8: Follows plans easily at 27 (sign of factor); plans to attend college at 15

Average Treatment Effect, Pooled: .33 (p−value: .06)
Average Treatment Effect, Females: .15 (p−value: .32)
Average Treatment Effect, Males: .39 (p−value: .07)
Figure 9: Invites friends home frequently at 15 (sign of factor); help others at 27

Average Treatment Effect, Pooled: .39 (p−value: .03)
Average Treatment Effect, Females: .44 (p−value: .12)
Average Treatment Effect, Males: .35 (p−value: .07)
Figure 10: Listens to music at 19 (sign of factor); reads magazines or newspapers at 40

Average Treatment Effect, Pooled: .34  (p−value: .04)
Average Treatment Effect, Females: .31 (p−value: .16)
Average Treatment Effect, Males: .38 (p−value: .06)
Figure 11: Uses computer at 40; registered to vote at 27 and 40

Average Treatment Effect, Pooled: .25 (p-value: .1)
Average Treatment Effect, Females: .36 (p-value: .11)
Average Treatment Effect, Males: .18 (p-value: .24)
Abecedarian Program
The Carolina Abecedarian Project

- **Where & When:**
  - Early intervention starting in the first months of life.

- **What:**
  - Full-day enriched center-based childcare (9 hours/day, 5 days/wk, 50 weeks/yr) for 5 years at age 0-5. Provided cognitive stimulation and education for developing self-control and social skills.
  - Bi-weekly home visits with individualized tutoring for 3 years at age 6-8 (but not during early childhood).
  - Health care (well-child checkups and ill-child medical care) was provided to the children attending the center-based program.
Similarly to Perry, the Abecedarian program was also designed to promote self-reinforcement among the children and reduce dependence on adult feedback (Ramey et al., 1982).

It was more intense than Perry combining a preschool component starting as early as at 6 weeks old and a school-age treatment through grade three.

The curriculum focused on “educational games” to build cognitive abilities (language, math, reading, writing), behavioral skills (attending behavior, task orientation, listening, task completion), and creativity and motor skills (through action songs, rhymes, story telling, fingerplays).
Carolina Abecedarian Project (ABC)

- Implemented years: 1972–1982
- 4 cohorts beginning at birth; 111 participants
- Target population fulfilled High Risk Index, including parents’ IQ, father at home, etc.
- Treatment lasted 5 years and included center-based care, formula, diapers, health check-ups, and medical care
• It also had a medical and nutritional component.
• The program produced lasting improvements in IQ (mostly for girls) because the interventions started very early in life (Campbell et al., 2001).
• Evidence suggests that IQ is more malleable in the very early childhood (Shonkoff and Phillips, 2000).
• Girls also showed a greater educational attainment, reduced participation in crime, decrease in substance abuse, and improved internalizing and externalizing behavior.
• Boys showed better health conditions and improvements in non-cognitive skills.
The Carolina Abecederian Project: Results
Figure 12: Number of people whom one can confide at 21 (sign of factor); gets emotional support from dad; close to parents at 21

Average Treatment Effect, Pooled: .44 (p-value: .02)
Average Treatment Effect, Females: .72 (p-value: .01)
Average Treatment Effect, Males: .23 (p-value: .21)
**Figure 13**: Incarcerated at 21; ever cited for breaking the law at 30 (sign of factor)

Average Treatment Effect, Pooled: \(-.11\) (p-value: .29)
Average Treatment Effect, Females: \(.07\) (p-value: .34)
Average Treatment Effect, Males: \(-.48\) (p-value: .08)
Figure 14: Education plans at 12 (sign of factor); high school at 30

Average Treatment Effect, Pooled: .43 (p-value: .02)
Average Treatment Effect, Females: .52 (p-value: .04)
Average Treatment Effect, Males: .34 (p-value: .12)
Figure 15: Child is sick at 7 and 10 (sign of factor)

Average Treatment Effect, Pooled: $-0.19$ (p-value: 0.19)
Average Treatment Effect, Females: $0.36$ (p-value: 0.12)
Average Treatment Effect, Males: $-0.75$ (p-value: 0)
The Abecedarian Intervention

Source: Campbell et al. (2014).
### ABC Health Effects Mid 30s: Males

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Control Mean</th>
<th>Treatment Mean</th>
<th>Permutation p-value</th>
<th>Stepdown p-value</th>
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<tr>
<td>Diastolic Blood Pressure</td>
<td>92.000</td>
<td>78.526</td>
<td>0.023</td>
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<td>Systolic Blood Pressure</td>
<td>143.333</td>
<td>125.789</td>
<td>0.020</td>
<td>0.033</td>
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<tr>
<td>Obesity &amp; Hypertension</td>
<td>0.500</td>
<td>0.111</td>
<td>0.016</td>
<td>0.016</td>
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<tr>
<td>Severe Obesity &amp; Hypertension</td>
<td>0.375</td>
<td>0.000</td>
<td>0.005</td>
<td>0.013</td>
</tr>
<tr>
<td>Hypertension &amp; Dyslipidemia</td>
<td>0.333</td>
<td>0.000</td>
<td>0.005</td>
<td>0.012</td>
</tr>
<tr>
<td>Vitamin D Deficiency</td>
<td>0.750</td>
<td>0.368</td>
<td>0.021</td>
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<tr>
<td>Framingham Risk Score</td>
<td>7.043</td>
<td>4.889</td>
<td>0.038</td>
<td>0.038</td>
</tr>
</tbody>
</table>

*Data: Abecedarian Program. Source: Campbell et al. (2014).*
The Jamaica Study: Grantham-McGregor et al. (Science, 2014)
• The Jamaican Supplementation study is an example of a childhood program offered in a less developed country with a long-term follow-up.

• It consists of two years of nutritional supplementation (milk formula) or stimulation (encouraged the mother to play with children in an effective manner) or both.

• The stimulation intervention appeared more effective.

• Now being applied more generally.
Both interventions stimulated short-term cognitive development, but only stimulation improved cognitive and character skills (in particular internalizing behavior) in the long run.

Stimulation also improved earnings and educational attainment (Gertler et al., 2013; Grantham-McGregor et al., 1991).
- Promoted parent-child interactions
- Consistent with the key features of early, more expensive programs
- Shows that less intensive programs can be effective
- Randomized study, sample of 129 children
- Stunted children between 9 and 24 months
- Designed to individualize the different effects of nutritional and cognitive stimulation
- Follow up to age 22
4 groups:

1. No intervention
2. Nutritional intervention only
3. Cognitive stimulation intervention only
4. Both cognitive and noncognitive interventions

Plus, a matched non-stunted group as a reference

The long lasting effects were found for the cognitive/socioemotional components of interventions.
Figure 16: Griffith developmental score in the period immediately after the intervention

*Griffith Scales tests for (a) locomotor (large muscle) skills, (b) hearing and speech, (c) hand/eye coordination, and (d) cognitive performance (shape recognition, block patterns, and block construction).
Findings:

- Fadeout effect of results on supplementation after 7 years of age
- The long lasting effects were found for the cognitive/socio-emotional components of interventions
- Stunted children remain in disadvantage for anthropometrics, cognitive capabilities as well as health capabilities
Table 3: Impact of Stimulation Treatment on Log Earnings

<table>
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<tr>
<th></th>
<th>I. Observed Sample</th>
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<tr>
<td></td>
<td>Treatment Effect</td>
<td>Stepdown p-value*</td>
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<tr>
<td><strong>A. First Job</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>0.27</td>
<td>0.11</td>
</tr>
<tr>
<td>Full Time</td>
<td>0.35</td>
<td>0.06</td>
</tr>
<tr>
<td>Non-Temporary</td>
<td>0.53</td>
<td>0.03</td>
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<tr>
<td><strong>B. Last Job</strong></td>
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<tr>
<td>All</td>
<td>0.27</td>
<td>0.06</td>
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<tr>
<td>Full Time</td>
<td>0.40</td>
<td>0.01</td>
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<tr>
<td>Non-Temporary</td>
<td>0.50</td>
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<td><strong>C. Current Job</strong></td>
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<tr>
<td>All</td>
<td>0.27</td>
<td>0.09</td>
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<tr>
<td>Full Time</td>
<td>0.43</td>
<td>0.02</td>
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<td>Non-Temporary</td>
<td>0.44</td>
<td>0.02</td>
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<td><strong>D. Average Earnings</strong></td>
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<tr>
<td>All</td>
<td>0.40</td>
<td>0.01</td>
</tr>
<tr>
<td>Full Time</td>
<td>0.34</td>
<td>0.01</td>
</tr>
<tr>
<td>Non-Temporary</td>
<td>0.47</td>
<td>0.01</td>
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</table>

* Adjusts for multiple hypothesis testing.

Source: Gertler et al. (2014).
Table 4: Impact of Treatment on Education and Skills

<table>
<thead>
<tr>
<th>Sample Size</th>
<th>Control Mean</th>
<th>Treatment Effect</th>
<th>Stepdown p-value</th>
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</thead>
<tbody>
<tr>
<td>A. Schooling</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>In school</td>
<td>97</td>
<td>0.15</td>
<td>0.17</td>
</tr>
<tr>
<td>In school full time</td>
<td>97</td>
<td>0.07</td>
<td>0.18</td>
</tr>
<tr>
<td>B. Skills</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cognitive factor</td>
<td>102</td>
<td>-0.46</td>
<td>0.59</td>
</tr>
<tr>
<td>Externalizing Behavior factor</td>
<td>102</td>
<td>-0.23</td>
<td>0.22</td>
</tr>
<tr>
<td>Internalizing Behavior factor</td>
<td>102</td>
<td>-0.32</td>
<td>0.39</td>
</tr>
<tr>
<td>Ever expelled from school</td>
<td>105</td>
<td>0.17</td>
<td>-0.12</td>
</tr>
</tbody>
</table>
Replication of Jamaica
Colombian Early Childhood Intervention: Design

- **Target population:** Children between 12 and 24 months living in families receiving the Colombian CCT program (Familias en Accion). The program targets the poorest 20% of households in the country.

- **Duration:** Lasted 18 months, starting in early 2010.

- **Stimulation curriculum:** Based on the Jamaican home visiting model culturally adapted for Colombia. The aims of the home visits were to improve the quality of maternal-child interactions and to assist mothers to participate in developmentally-appropriate learning activities, centered around daily routines and using household resources.

- **Micronutrient supplementation:** The micronutrient supplementation consisted of Sprinkles—encapsulated micronutrients in powder form—developed to treat childhood anemia.

Colombian Early Childhood Intervention: Design

- **Evaluation Strategy:** clustered randomized control trial within each of the three large regions:
  - 32 municipalities were randomly assigned to one of 4 groups: (i) psychosocial stimulation, (ii) micronutrient supplementation, (iii) both, and (iv) control.
  - Assignment to treatment was via cluster-level randomization. In each municipality, 3 Madre Lideres (MLs) were selected and the children of the beneficiary households represented by each of these MLs were recruited to the study.

- **Sample:** 1,429 children living in 96 towns in three regions in central Colombia.

- **Surveys and follow ups:** Baseline survey before the intervention started and a follow-up survey when it ended 18 months later

*Source: Attanasio et. al (2015).*
Colombian Early Childhood Intervention: Short-Term Impacts

- The psychosocial stimulation program delivered through home visits significantly improved the cognitive and socio-emotional development of disadvantaged children.
- Micronutrient supplementation had no significant effect on any outcomes.
- The effects of the program can be fully explained by increases in parental investments (material and time), which have strong effects on outcomes and are complementary to both maternal skills and child’s past skills.

Link to
Details on Attanasio Group Application
The Nurse-Family Partnership Program
The Nurse-Family Partnership (NFP) is a program targeted at low-income, unmarried, and/or adolescent mothers.

It consists of nurse visits to young mothers from the first or second trimester of the mother’s first pregnancy until the second birthday of her first child.

The program encourages mothers to reduce smoking, teaches them how to take care of their children and helps them to pursue education and find jobs.
• Evaluated exploiting the random assignment, the program benefits children.

• The treated group exhibits persistent higher IQ scores through age 6 (Olds et al., 2007), lower rate of substance abuse and lower levels of internalizing behavior (e.g., anxiety, depression and, withdrawal) by age 12 (Kitzman et al., 2010) and lower propensity to engage in crime by age 19 (Eckenrode et al., 2010).
### Table 5: NFP Memphis, Parental Responses (Females)

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Age (years)</th>
<th>Sample Size</th>
<th>Conditional Effect Size</th>
<th>Asymptotic p-values</th>
<th>Permutation Single p-val</th>
<th>Freedman-Lane Stepdown</th>
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Table 6: NFP Memphis, Parental Responses (Males)

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*Source: Moon (2013).*
Evidence from Head Start
Overview of Head Start

- Evidence comes from the Head Start Impact Study (HSIS) and nationally-representative datasets
- Comparable with and bridge the gap between Demonstration and Universal Programs
Limitations in the Evidence on Head Start

- Heterogeneous Populations and Treatment Alternatives
- Lack of Long-Term Follow-up
- Control contamination
Two recent and preliminary studies address control for contamination in HSIS (Feller et al., 2016; Kline and Walters, 2014).

They relate their estimates to theoretical parameters in order to answer well-defined and relevant policy questions Feller et al. (2016); Kline and Walters (2014).

Both studies provide estimates of the average treatment effects in Head Start compared directly to the different alternatives available used by parents: (i) other preschool programs and (ii) staying at home.

“Compliers” in the sense of LATE (20%).

The magnitudes of their preferred estimates on cognition are relatively different: 0.23 of a standard deviation in Feller et al. (2016) and 0.38 of a standard deviation in Kline and Walters (2014).
Link: Review of Literature
Head Start provides heterogeneous treatment to heterogeneous populations. Therefore, it is crucial that researchers study the available alternatives in the settings where children take-up treatment. Such an analysis provides meaning for estimates reported in the literature.

Strategies accounting for control contamination – i.e., control group families that find alternative early childhood education environments – show that the effects of Head Start on cognition are positive and sizable, though they fade out. This evidence is usually based on the randomized, controlled trial designed to evaluate Head Start, the Head Start Impact Study.
Studies evaluating long-term outcomes from Head Start find that the program has persistent beneficial effects on important outcomes such as health and education. Thus, even if the effects on cognition fade out, Head Start has positive outcomes on broader measures describing the socioeconomic life of an individual. This evidence is based on nationally-representative data sets.

Crude cost-benefit analyses of Head Start suggest that the program could be socially efficient. More comprehensive evaluations could imply high internal rates of returns, as current calculations include only gains in earnings.
Evidence from Large-Scale Early Childhood Programs
Overview

Three Types of Programs

• Universal subsidies for childcare (international programs with long-term follow-up)
• Local universal programs (center-based, domestic programs with short-term follow-up)
• Local means-tested program (center-based, domestic program with short-term follow-up)

Three Major Insights

• Universal programs do not imply universal take-up.
• Disadvantaged children benefit the most from universal programs
• High quality programs benefit children, while lower quality ones may have negative effects
Universal Subsidies to Childcare

- **Norway Kindergarten Act:**
  - Havnes and Mogstad (2011) find positive effects long-term educational attainment and economic outcomes
  - Havnes and Mogstad (2015) find that disadvantaged children benefit the most

- **Quebec Childcare Reform:**
  - Baker et al. (2008) find that effects on child behavior and parent-child interactions are negative
  - Baker et al. (2015) find positive effects on non-cognitive skills for disadvantaged children and favorable effects on teenage criminal activity
  - The program increased maternal labor supply for higher-income families
Local Universal Programs in the US

- Boston, Georgia, and Oklahoma
- Various studies about the effects:
  Cascio and Schanzenbach (2013), Gormley and Gayer (2005),
  Gormley et al. (2005), Weiland and Yoshikawa (2013)
- In general, there are positive short-term impacts on
  achievement for free-lunch eligible children
Local Means-Tested Programs in the US

- Tennessee Voluntary Prekindergarten Program (TN-VPK)
- Evaluation through a randomized control trial with two major flaws:
  1. Selective attrition
  2. Control contamination
- Non-Experimental methods fail to account for:
  1. Multiplicity of skills
  2. Fadeout as a potential result of the control group catching up
The Importance of Quality

- Non-center-based childcare has negative effects on cognition compared to center-based childcare
- Effects of childcare and time spent with mothers on cognition are roughly equivalent in absolute value
- Bernal (2008), Bernal and Keane (2011), García et al. (2014)
1. A comprehensive evaluation considers multiple skills and outcomes. Cognition, as measured by IQ, fades out. However, early life non-cognitive skills mediate skills later in life, affecting relevant socioeconomic outcomes such as education, employment, health, and criminal activity.

2. Methodology to assess demonstration programs with compromised randomizations, small sample sizes, and attrition is available, and applying it shows that demonstration programs have positive effects over the life-cycle. These effects survive conservative tests accounting for multiple hypotheses inference.

3. When evaluated comprehensively, demonstration programs targeting **disadvantaged** populations are socially efficient, as measured by their internal rates of return.
### Table 7: Summary of Effects for Main Interventions

<table>
<thead>
<tr>
<th>Program</th>
<th>Age</th>
<th>Duration</th>
<th>Target</th>
<th>Selection</th>
<th>Follow-Up</th>
<th>Sample</th>
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## Table 7: Summary of Effects for Main Interventions

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Table 7: Summary of Effects for Main Interventions

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Elementary School and Adolescent Programs
### Table 7: Summary of Effects for Main Interventions

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<th>Duration</th>
<th>Target</th>
<th>Selection</th>
<th>Follow-Up</th>
<th>Sample</th>
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Table 7: Summary of Effects for Main Interventions

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<th>Health</th>
<th>Parental</th>
<th>On Site</th>
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<td>Year-Up</td>
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<tr>
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<tr>
<td><strong>Elementary</strong></td>
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<td>LA’s Best</td>
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<td>SSDP</td>
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<td><strong>Adolescence</strong></td>
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<td>STEP</td>
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<td>Academies</td>
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<td>Job Corps</td>
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<td>Year-Up</td>
<td>.</td>
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</tr>
</tbody>
</table>
Educational and Adolescent Programs
The Montreal Longitudinal Experimental Study (MLES)
Cambridge-Somerville Program
Project STAR
Education and Interventions Targeted Toward Adolescents and Young Adults
Adolescent Mentorship Programmes
• Quantum Opportunity Program
• Becoming a Man
• Pathways to Education Programme
• Empresários Pela Inclusão Social (EPIS) Program
• H&R Block FAFSA experiment
• Dartmouth College Coaching Program
Residential-Based Programmes
- Job Corps
- National Guard ChalleNGe
Work-Based Adolescent Intervention Programmes

- Career Academies
Table 8: Summary of Treatment Effects from Career Academies within 96-Month Follow-Up after Scheduled High School Graduation

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Males</th>
<th>Females</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Labor Market (49–96 Months)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monthly Earnings ($)(^{(a)})</td>
<td>361**</td>
<td>118</td>
</tr>
<tr>
<td>Months Employed (#)</td>
<td>2.8***</td>
<td>−0.3</td>
</tr>
<tr>
<td>Average Hours Worked per Week (#)</td>
<td>4.1***</td>
<td>0.2</td>
</tr>
<tr>
<td>Average Hourly Wages ($)</td>
<td>0.6</td>
<td>0.7</td>
</tr>
<tr>
<td><strong>Educational Attainment (After 96 Months)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High School Diploma</td>
<td>−0.4</td>
<td>0.2</td>
</tr>
<tr>
<td>GED</td>
<td>3.6</td>
<td>1.3</td>
</tr>
<tr>
<td>Certificate/License</td>
<td>2.0</td>
<td>0.1</td>
</tr>
<tr>
<td>AA Degree</td>
<td>−1.0</td>
<td>1.8</td>
</tr>
<tr>
<td>BA Degree</td>
<td>−2.2</td>
<td>−1.6</td>
</tr>
<tr>
<td><strong>Family Formation (After 96 Months)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married and Living Together</td>
<td>9.0**</td>
<td>1.5</td>
</tr>
<tr>
<td>Custodial Parent</td>
<td>11.5***</td>
<td>3.7</td>
</tr>
<tr>
<td>Non-Custodial Parent</td>
<td>−6.4**</td>
<td>0.2</td>
</tr>
</tbody>
</table>
Year-Up Programme

- Self-Sufficiency Project
- Apprenticeship Programmes
Other Curricula That Have Been Applied to Multiple Age Groups
Tools of the Mind
Studies that Teach the Incremental Theory of Intelligence
The Seattle Social Development Project (SSDP)
### Table 9: Summary of Treatment Effects from the Seattle Social Development Project

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Age 18&lt;sup&gt;(h)&lt;/sup&gt;</th>
<th>Age 21&lt;sup&gt;(i)&lt;/sup&gt;</th>
<th>Age 24&lt;sup&gt;(j)&lt;/sup&gt;</th>
<th>Age 27&lt;sup&gt;(j)&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPA</td>
<td>0.24*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAT(ES)&lt;sup&gt;(a)&lt;/sup&gt;</td>
<td>0.05</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grade Repetition(%)</td>
<td>−8.7**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dropout(%)</td>
<td>−7.3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>School Misbehavior&lt;sup&gt;(b)&lt;/sup&gt;</td>
<td>−1.41**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Violent Crime(%)</td>
<td>−11.4**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ever Arrested(%)</td>
<td>−6.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Arrested past year(%)</td>
<td>−2.0</td>
<td>1.0</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Smoking(%)</td>
<td>−0.7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pregnancy(%)</td>
<td>−9.3*</td>
<td>−9.0</td>
<td>−8.0</td>
<td></td>
</tr>
<tr>
<td>Anxiety&lt;sup&gt;(c)&lt;/sup&gt;</td>
<td>−2.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression&lt;sup&gt;(c)&lt;/sup&gt;</td>
<td>−8.0*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High School Graduate/GED(%)</td>
<td>10.0***</td>
<td>6.0</td>
<td>6.0</td>
<td></td>
</tr>
<tr>
<td>More than 2 Years of College(%)</td>
<td>8.0***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Self-efficacy&lt;sup&gt;(d)&lt;/sup&gt;</td>
<td>0.17***</td>
<td>0.13*</td>
<td>−0.01</td>
<td></td>
</tr>
<tr>
<td>Associate’s Degree(%)</td>
<td></td>
<td>12.0*</td>
<td>12.0*</td>
<td></td>
</tr>
<tr>
<td>Bachelor’s Degree(%)</td>
<td></td>
<td>7.0</td>
<td>6.0</td>
<td></td>
</tr>
<tr>
<td>Substance Abuse Index&lt;sup&gt;(e)&lt;/sup&gt;</td>
<td></td>
<td>3.0</td>
<td>−3.0</td>
<td></td>
</tr>
<tr>
<td>Mental Health Disorder Index&lt;sup&gt;(f)&lt;/sup&gt;</td>
<td>−9.0*</td>
<td>−11.0**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income(in thousands)&lt;sup&gt;(g)&lt;/sup&gt;</td>
<td></td>
<td>3.51</td>
<td></td>
<td>3.12</td>
</tr>
</tbody>
</table>
The Effects of Education and Parental Investment of Cognitive and Non-Cognitive Skill
• Boosting the capabilities of children \textit{entering} school boosts the benefits of education for them.
Early development is as important as education in promoting wages, employment, and health.
Beneficial Causal Outcomes of Education at Different Stages

1. Self reported health
2. Voting
3. Trust
4. Employment
5. Wages
6. Participation in welfare
7. Depression
8. Self-esteem
9. Incarceration
10. Health related work limitations
11. Smoking
12. White-collar employment
“Returns to Education: The Causal Effects of Education on Earnings, Health and Smoking”
by James J. Heckman, John Eric Humphries, and Greg Veramendi
(Forthcoming in JPE, 2016)
Figure 17: Effects of Education at Various Stages on Outcomes

Figure 17: Effects of Education at Various Stages on Outcomes (Cont.)

Figure 17: Effects of Education at Various Stages on Outcomes (Cont.)

Treatment Effects: Voted in 2006

Treatment Effects: Trusts People

Figure 17: Effects of Education at Various Stages on Outcomes (Cont.)

Treatment Effects: Log Wages

Treatment Effects: Log PV Wages

Figure 17: Effects of Education at Various Stages on Outcomes (Cont.)

Treatment Effects: Daily Smoking

Treatment Effects: Health Limits Work

Sorting on Ability

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Low Ability</th>
<th>High Ability</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_1$: Dropping from HS vs. Graduating from HS</td>
<td>0.31</td>
<td>0.31</td>
</tr>
<tr>
<td>$D_2$: HS Graduate vs. College Enrollment</td>
<td>0.22</td>
<td>0.38</td>
</tr>
<tr>
<td>$D_3$: Some College vs. 4-year college degree</td>
<td>0.13</td>
<td>0.51</td>
</tr>
</tbody>
</table>

Figure 18: Average Treatment Effect of Education on Log Wages at Age 30, by Decision Node and Endowment Levels

A. Graduating from HS vs. Dropping from HS

Source: Heckman et al. (2016b).
Figure 18: Average Treatment Effect of Education on Log Wages at Age 30, by Decision Node and Endowment Levels, Cont’d

B. Getting a GED vs. HS Dropout

Source: Heckman et al. (2016b).
Figure 18: Average Treatment Effect of Education on Log Wages at Age 30, by Decision Node and Endowment Levels, Cont’d

C. College Enrollment vs. HS Graduate

Source: Heckman et al. (2016b).
Figure 18: Average Treatment Effect of Education on Log Wages at Age 30, by Decision Node and Endowment Levels, Cont’d

D. Four-Year College Degree vs. Some College

Source: Heckman et al. (2016b).
Figure 19: Average Treatment Effect of Education on Present Value of Wages, by Decision Node and Endowment Levels

A. Graduating from HS vs. Dropping from HS

Source: Heckman et al. (2016b).
Figure 19: Average Treatment Effect of Education on Present Value of Wages, by Decision Node and Endowment Levels, Cont’d

B. Getting a GED vs. HS Dropout

Source: Heckman et al. (2016b).
Figure 19: Average Treatment Effect of Education on Present Value of Wages, by Decision Node and Endowment Levels, Cont’d

C. College Enrollment vs. HS Graduate

Source: Heckman et al. (2016b).
Figure 19: Average Treatment Effect of Education on Present Value of Wages, by Decision Node and Endowment Levels, Cont’d

D. Four-Year College Degree vs. Some College

Source: Heckman et al. (2016b).
Link to Further Results
Figure 20: Causal Effect of Schooling on ASVAB Measures of Cognition

(a) Arithmetic Reasoning

(b) Word Knowledge

Source: Heckman et al. (2006, Figure 4).
Figure 20: Causal Effect of Schooling on ASVAB Measures of Cognition

(c) Paragraph Comprehension

(d) Math Knowledge

Source: Heckman et al. (2006, Figure 4).
Figure 20: Causal Effect of Schooling on ASVAB Measures of Cognition

(e) Coding Speed

\[ \text{Mean value of test score, covariates fixed at mean} \]

\[ \text{Less than 12} \quad 12 \quad 13-15 \quad 16 \text{ or more} \]

Source: Heckman et al. (2006, Figure 4).
Character Can Be Fostered

- See OECD report
Point 1: Considerable Evidence That Early Programs Are Effective

- As a group, early childhood programs have been shown to be more effective than later stage programs.
- Adolescent programs are less well-studied and the evidence on them is mixed.
- Adolescent interventions that teach personality skills in the workplace (or specific context) are promising.
Point 2: Long-Term Follow-Ups Are Vital

- Many programs have short-term effects but no long-term effects.
- Others have no short-term effects (for some measures) but long-term effects.
Point 3: Non-Cognitive Skills Are Important Channels of Childhood Benefits Throughout Early Childhood and Adolescence

- Only interventions that started before age 3 had a long-term effect on IQ
- Many interventions starting after age 3 have effectively improved outcomes by improving non-cognitive skills
- Adolescent interventions that teach personality skills in the workplace (or specific context) are promising
Point 4: Parenting Is a Main Mechanism Through which the Programs Have an Effect
END
Details on Attanasio Group Application
Table 10: Short-term Impacts of Psycho-social Stimulation on Cognition, Language, and Find Motor Development; Child Temperament; and Parental Investments

Notes: The unit of observation is the child. Coefficients and standard errors (in parentheses) from a regression of the dependent variable measured at follow-up on the intervention variable (a treatment dummy for psychosocial stimulation, combining children receiving stimulation alone and children receiving both stimulation and micro-nutrient supplementation) controlling for: child’s sex; baseline level of the outcome (except for MacArthur-Bates “Complex sentences”, where we control for baseline number of words spoken because the item measuring “Complex sentences” was not measured at baseline); and tester dummies. Standard errors are adjusted for clustering at the municipality level. **, * and + indicate significance at 1, 5, and 10%. All scores have been internally standardized non-parametrically for age and are therefore expressed in standard deviations (see Appendix B for details about the measures and the standardization procedure).

Source: Attanasio et. al (2015).

<table>
<thead>
<tr>
<th>Instrument:</th>
<th>Bayley</th>
<th>MacArthur-Bates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Item:</td>
<td>Cognitive</td>
<td>Language receptive</td>
</tr>
<tr>
<td>Treatment effect</td>
<td>0.244**</td>
<td>0.175**</td>
</tr>
<tr>
<td></td>
<td>(0.0621)</td>
<td>(0.0647)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,264</td>
<td>1,264</td>
</tr>
</tbody>
</table>
Table 10: Short-term Impacts of Psycho-social Stimulation on Cognition, Language, and Find Motor Development; Child Temperament; and Parental Investments

<table>
<thead>
<tr>
<th>Instrument Item</th>
<th>Bates Unsociable</th>
<th>Bates Difficult</th>
<th>Bates Unadaptable</th>
<th>Bates Unstoppable</th>
<th>Family Care Indicators (FCI) Varieties of play materials</th>
<th>Family Care Indicators (FCI) Varieties of play activities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment</td>
<td>-0.0433</td>
<td>-0.0758+</td>
<td>0.0597</td>
<td>-0.0313</td>
<td>0.213**</td>
<td>0.273**</td>
</tr>
<tr>
<td></td>
<td>(0.0549)</td>
<td>(0.0455)</td>
<td>(0.0615)</td>
<td>(0.0535)</td>
<td>(0.0637)</td>
<td>(0.0499)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,326</td>
<td>1,326</td>
<td>1,326</td>
<td>1,326</td>
<td>1,326</td>
<td>1,326</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is the child. Coefficients and standard errors (in parentheses) from a regression of the dependent variable measured at follow-up on the intervention variable (a treatment dummy for psychosocial stimulation, combining children receiving stimulation alone and children receiving both stimulation and micro-nutrient supplementation) controlling for: child’s sex; baseline level of the outcome (except for MacArthur-Bates “Complex sentences”, where we control for baseline number of words spoken because the item measuring “Complex sentences” was not measured at baseline); and tester dummies. Standard errors are adjusted for clustering at the municipality level. **, * and + indicate significance at 1, 5, and 10%. All scores have been internally standardized non-parametrically for age and are therefore expressed in standard deviations (see Appendix B for details about the measures and the standardization procedure).

Source: Attanasio et. al (2015).
Figure 21: Kernel Densities of Latent Factors, baseline

Notes: These kernel densities are constructed using 10,000 draws from the estimated joint distribution of latent factors for the control group and for the treated group. 
Source: Attanasio et. al (2015).
Figure 22: Kernel Densities of Latent Factors, follow up

Notes: These kernel densities are constructed using 10,000 draws from the estimated joint distribution of latent factors for the control group and for the treated group. 
Source: Attanasio et. al (2015).
Figure 23: Kernel Densities of Latent Factors, investments

Notes: These kernel densities are constructed using 10,000 draws from the estimated joint distribution of latent factors for the control group and for the treated group. Source: Attanasio et. al (2015).
Figure 24: Marginal product of time investments in the production of socio-emotional skills

Source: Attanasio et. al (2015).
Figure 25: Marginal product of material investments in the production of cognitive skills

Source: Attanasio et. al (2015).
Hogares Comunitarios de Bienestar

- Hogares Comunitarios de Bienestar (HCB) is a home-based child care program in Colombia. The program delivers home-based child care, supplemental nutrition, and psychosocial stimulation to about 800K low-income children under the age of 5 (32% of eligible children).

- Participating parents are required to pay a monthly fee up to 25% of daily minimum wage. Traditional HCB child care homes are led by a communitarian mother (MC).

- Bernal et al. (2009) and Bernal and Fernandez (2013) have identified care providers as having, on average, low education levels and not being appropriately trained for the provision of child care. Therefore, the effects of the program effects were significantly lower than its potential effect.

*Source:* Bernal 2015.
In 2007, a vocational education program was introduced which offers a degree in child development for child care providers.

Bernal 2015 evaluates the effects of this program on the quality of care provided and on the nutritional and health status, as well as cognitive and socio-emotional development of beneficiary children in Bogotá.

**Evaluation Strategy:** In September 2009, a call for program participation was issued in 3 neighborhoods in Bogotá. Out of 198 MCs, 80 were randomly selected to the study sample. The assignment to treatment was not random. The propensity score matching was used to match MCs in the treatment and the control.

**Sample:** Total 140 HCBs: 67 treated and 73 controls. Total of 1579 children: 771 children in treated HSBs and 808 beneficiary children in untreated HSBs.

*Source:* Bernal 2015.
Hogares Comunitarios de Bienestar

The short term impacts indicate that:

- Quality of care has increased significantly. In particular, the implementation of learning activities, the use of pedagogical resources, and interactions between parents and care providers have increased.

- There is positive and significant effects for treated beneficiary:
  - Positive effects on children’s health, in particular for incidence of cough, flu and cold of approximately 5 percentage points.
  - Positive effects on the socio-emotional development of children of approximately 0.17SD.
  - Positive effects on cognitive development of approximately 0.4 SD for children younger than 3 years old and 0.2 SD for children older than 3 years.

- The cost benefit ratio of the vocational training ranges from 3 to 11, depending on the discount rate.

Source: Bernal 2015.
**Figure 26: Program Effects on Beneficiary Children Estimated**

<table>
<thead>
<tr>
<th>Outcome variable</th>
<th>Control group</th>
<th>Complete treatment group</th>
<th>Only MC treated in 2008c</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std dev</td>
<td>Effect</td>
</tr>
<tr>
<td>Health</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Health summary index</td>
<td>0.00</td>
<td>(0.64)</td>
<td>0.082</td>
</tr>
<tr>
<td>Incidence of diarrhea (%)</td>
<td>0.02</td>
<td>(0.13)</td>
<td>-0.018</td>
</tr>
<tr>
<td>Incidence of cough, flu, cold (%)</td>
<td>0.11</td>
<td>(0.31)</td>
<td>-0.045</td>
</tr>
<tr>
<td>Psychosocial development</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Psychosocial summary index</td>
<td>0.04</td>
<td>(0.84)</td>
<td>-0.03</td>
</tr>
<tr>
<td>PIPPS—Aggression</td>
<td>2.01</td>
<td>(0.46)</td>
<td>0.12</td>
</tr>
<tr>
<td>PIPPS—Isolation</td>
<td>1.54</td>
<td>(0.42)</td>
<td>0.16</td>
</tr>
<tr>
<td>Cognitive development</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cognitive summary index</td>
<td>0.00</td>
<td>(2.59)</td>
<td>-0.08</td>
</tr>
<tr>
<td>ASQ—Communication (score)</td>
<td>46.35</td>
<td>(12.62)</td>
<td>2.20</td>
</tr>
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<td>Risk of communication lag</td>
<td>0.12</td>
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<td>-0.04</td>
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<td>ASQ—Problem solving (score)</td>
<td>46.61</td>
<td>(11.78)</td>
<td>-0.15</td>
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<td>Risk of problem solving lag</td>
<td>0.08</td>
<td>(0.27)</td>
<td>-0.04</td>
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<td>ASQ—Cognitive</td>
<td>92.96</td>
<td>(20.95)</td>
<td>2.05</td>
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<td>Psychomotor development</td>
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<td>Psychomotor summary index</td>
<td>0.00</td>
<td>(1.70)</td>
<td>-0.34</td>
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<td>ASQ—Fine motor skills</td>
<td>42.45</td>
<td>(14.53)</td>
<td>-4.66</td>
</tr>
<tr>
<td>Risk of fine motor lag</td>
<td>0.07</td>
<td>(0.26)</td>
<td>0.08</td>
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*Source: Bernal 2015.*
Return to main text
Review of Literature
Table 11: Evidence Across Studies of the Impacts of Head Start

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<tr>
<td>Impacts</td>
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<tr>
<td>IQ/achievement, ages 3-4</td>
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<tr>
<td>Behavior, ages 3-4</td>
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<td>-</td>
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<td>0.46 (0.129)</td>
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<td>Grade retention ever</td>
<td>-0.008 (0.098)</td>
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<td>0.117</td>
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<tr>
<td>Attended some college</td>
<td>-</td>
<td>0.031 (0.071)</td>
<td>0.028 (0.080)</td>
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Heckman Interventions
Table 11: Evidence Across Studies of the Impacts of Head Start, Cont’d

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<th>Years of birth</th>
<th>Impacts</th>
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<td>1998-1999</td>
<td>0.230 (0.038)</td>
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<tr>
<td>Kline and Walters (2014)</td>
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<td>1998-1999</td>
<td>0.375 (0.047)</td>
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<td>IQ/achievement, ages 3-4</td>
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<tr>
<td>Behavior, ages 3-4</td>
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<td>IQ/achievement, ages 5-6</td>
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<td>-</td>
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<td>0.287 (0.095)</td>
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<td>0.031 (0.076)</td>
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<td>Grade retention ever</td>
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<td>-1.07 (0.056)</td>
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<td>High School grad. (no GED)</td>
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<td>0.067 (0.044)</td>
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<td>0.136</td>
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<td>0.049</td>
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<td>Perry Preschool (Various sources)</td>
<td>Abecedarian (Various sources)</td>
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<td>98% AA, low mother IQ, &amp; low SES</td>
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<td>1972-1977</td>
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<td>Years of birth</td>
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<tr>
<td>Impacts</td>
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<tr>
<td>IQ/achievement, ages 3-4</td>
<td>0.30&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
<td>0.880&lt;sup&gt;b&lt;/sup&gt; (0.147)</td>
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<tr>
<td>Behavior, ages 3-4</td>
<td>0.35–0.19&lt;sup&gt;a&lt;/sup&gt;</td>
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<td></td>
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<tr>
<td>IQ/achievement, ages 5-6</td>
<td></td>
<td>0.763&lt;sup&gt;c&lt;/sup&gt; (0.127)</td>
<td>0.427&lt;sup&gt;c&lt;/sup&gt; (0.227)</td>
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<tr>
<td>IQ/achievement, ages 7-21</td>
<td></td>
<td>0.084&lt;sup&gt;c&lt;/sup&gt; (0.059)</td>
<td>0.300&lt;sup&gt;c&lt;/sup&gt; (0.213)</td>
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<tr>
<td>Grade retention ever</td>
<td></td>
<td></td>
<td>-0.244&lt;sup&gt;b&lt;/sup&gt; (0.151)</td>
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<td>High School grad. (no GED)</td>
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<td>0.56&lt;sup&gt;d&lt;/sup&gt; (0.093)</td>
<td>0.185&lt;sup&gt;b&lt;/sup&gt; (0.210)</td>
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Table 11: Evidence Across Studies of the Impacts of Head Start, Cont’d

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<td>Impacts</td>
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<td>Earnings, ages 23-40</td>
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<td>Idle</td>
<td>-</td>
<td>(0.357)</td>
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<td>Ever booked crime</td>
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<td>Depression Scale, ages 16-17</td>
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Note: The table continues with more data on impacts across different studies.
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<td>Impacts</td>
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<td></td>
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<tr>
<td>Earnings, ages 23-40</td>
<td>-</td>
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<tr>
<td>Idle</td>
<td>-0.030</td>
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<tr>
<td></td>
<td>(0.053)</td>
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<tr>
<td>Ever booked crime</td>
<td>0.051</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<td>0.050</td>
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<td></td>
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<td>(0.053)</td>
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<td>Behavior Index, ages 12-13</td>
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<td></td>
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<td>(0.582)</td>
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<td>Depression Scale, ages 16-17</td>
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<td></td>
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<td>(0.489)</td>
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### Table 11: Evidence Across Studies of the Impacts of Head Start, Cont’d

<table>
<thead>
<tr>
<th>Study</th>
<th>Zhai et al. (2014)</th>
<th>Perry Preschool (Various sources)</th>
<th>Abecedarian (Various sources)</th>
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<td><strong>Dataset</strong></td>
<td>HSIS</td>
<td>AA, low child IQ at entry &amp; SES</td>
<td>98% AA, low mother IQ, &amp; low SES</td>
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<td><strong>Impacts</strong></td>
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<td>-</td>
<td>$6,166^d$</td>
<td>$8,499^b$</td>
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<td>Idle</td>
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<td>(8244)</td>
<td>(8018)</td>
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<td>Ever booked crime</td>
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<td>-5.739^b</td>
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<td>(1.590)</td>
<td>(4.250)</td>
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<td>Depression Scale, ages 16-17</td>
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Further Results
Figure 27: Average Treatment Effect of Education on Smoking, by Decision Node and Endowment Levels

A. Graduating from HS vs. Dropping from HS

Source: Heckman et al. (2016b).
Figure 27: Average Treatment Effect of Education on Smoking, by Decision Node and Endowment Levels, Cont’d

B. Getting a GED vs. HS Dropout

Source: Heckman et al. (2016b).
Figure 27: Average Treatment Effect of Education on Smoking, by Decision Node and Endowment Levels, Cont’d

C. College Enrollment vs. HS Graduate

Source: Heckman et al. (2016b).
Figure 27: Average Treatment Effect of Education on Smoking, by Decision Node and Endowment Levels, Cont’d

D. Four-Year College Degree vs. Some College

Source: Heckman et al. (2016b).
Figure 28: Average Treatment Effect of Education on Health Limits Work, by Decision Node and Endowment Levels

A. Graduating from HS vs. Dropping from HS

Source: Heckman et al. (2016b).
Figure 28: Average Treatment Effect of Education on Health Limits Work, by Decision Node and Endowment Levels, Cont’d

B. Getting a GED vs. HS Dropout

Source: Heckman et al. (2016b).
Figure 28: Average Treatment Effect of Education on Health Limits Work, by Decision Node and Endowment Levels, Cont’d

C. College Enrollment vs. HS Graduate

Source: Heckman et al. (2016b).
Figure 28: Average Treatment Effect of Education on Health Limits Work, by Decision Node and Endowment Levels, Cont’d

D. Four-Year College Degree vs. Some College

Source: Heckman et al. (2016b).
### Table 12: Tests on The Estimated Factor Loadings on Cognitive and Socio-Emotional Factors by Outcome and Schooling Level

<table>
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<th>Variables</th>
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<tr>
<td></td>
<td>$p$-val$^{(a)}$</td>
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<td>Log Wages</td>
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<tr>
<td>Cognitive</td>
<td>0.000</td>
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<tr>
<td>Socio-Emotional</td>
<td>0.224</td>
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<tr>
<td>Log PV Wages</td>
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<tr>
<td>Cognitive</td>
<td>0.000</td>
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<tr>
<td>Socio-Emotional</td>
<td>0.054</td>
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<tr>
<td>Smoking (Age 30)</td>
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<td>Cognitive</td>
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<td>Socio-Emotional</td>
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<td>Health Limits Work</td>
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<td>Cognitive</td>
<td>0.000</td>
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<tr>
<td>Socio-Emotional</td>
<td>0.202</td>
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</table>

**Notes:** (a) shows $p$-values from a likelihood ratio test against the null hypothesis that the factor loadings for the conditional models are jointly equal to zero. (b) shows the $p$-value from a likelihood ratio test against the null hypothesis that the factor loadings for the conditional models are jointly equal.
Figure 29: The Effect of Cognitive and Socio-Emotional Endowments on Log Wages (age 30)

A. Overall

Source: Heckman et al. (2016b).
Figure 29: The Effect of Cognitive and Socio-Emotional Endowments on Log Wages (age 30), Cont’d

B. High School Dropout

Source: Heckman et al. (2016b).
Figure 29: The Effect of Cognitive and Socio-Emotional Endowments on Log Wages (age 30), Cont’d

C. GED

Source: Heckman et al. (2016b).
Figure 29: The Effect of Cognitive and Socio-Emotional Endowments on Log Wages (age 30), Cont’d

D. High School Graduate

Source: Heckman et al. (2016b).
Figure 29: The Effect of Cognitive and Socio-Emotional Endowments on Log Wages (age 30), Cont’d

E. Some College

Source: Heckman et al. (2016b).
Figure 29: The Effect of Cognitive and Socio-Emotional Endowments on Log Wages (age 30), Cont’d

F. Four-Year College

Source: Heckman et al. (2016b).
Figure 30: The Effect of Cognitive and Socio-Emotional Endowments on Log Present Value Wages

A. All

Source: Heckman et al. (2016b).
Figure 30: The Effect of Cognitive and Socio-Emotional Endowments on Log Present Value Wages, Cont’d

B. High School Dropout

Source: Heckman et al. (2016b).
Figure 30: The Effect of Cognitive and Socio-Emotional Endowments on Log Present Value Wages, Cont’d

C. GED

Source: Heckman et al. (2016b).
Figure 30: The Effect of Cognitive and Socio-Emotional Endowments on Log Present Value Wages, Cont’d

D. High School Graduate

Source: Heckman et al. (2016b).
Figure 30: The Effect of Cognitive and Socio-Emotional Endowments on Log Present Value Wages, Cont’d

F. Four-Year College

Source: Heckman et al. (2016b).
Figure 31: The Effect of Cognitive and Socio-Emotional Endowments on Smoking (age 30)

A. All

Source: Heckman et al. (2016b).
Figure 31: The Effect of Cognitive and Socio-Emotional Endowments on Smoking (age 30), Cont’d

B. High School Dropout

Source: Heckman et al. (2016b).
Figure 31: The Effect of Cognitive and Socio-Emotional Endowments on Smoking (age 30), Cont’d

C. GED

Source: Heckman et al. (2016b).
Figure 31: The Effect of Cognitive and Socio-Emotional Endowments on Smoking (age 30), Cont’d

D. High School Graduate

Source: Heckman et al. (2016b).
Figure 31: The Effect of Cognitive and Socio-Emotional Endowments on Smoking (age 30), Cont’d

E. Some College

Source: Heckman et al. (2016b).
Figure 31: The Effect of Cognitive and Socio-Emotional Endowments on Smoking (age 30), Cont’d

F. Four-Year College

Source: Heckman et al. (2016b).
Figure 32: The Effect of Cognitive and Socio-Emotional Endowments on Health Limits Work

A. All

Source: Heckman et al. (2016b).
Figure 32: The Effect of Cognitive and Socio-Emotional Endowments on Health Limits Work, Cont’d

B. High School Dropout

Source: Heckman et al. (2016b).
Figure 32: The Effect of Cognitive and Socio-Emotional Endowments on Health Limits Work, Cont’d

C. GED

Source: Heckman et al. (2016b).
Figure 32: The Effect of Cognitive and Socio-Emotional Endowments on Health Limits Work, Cont’d

D. High School Graduate

Source: Heckman et al. (2016b).
Figure 32: The Effect of Cognitive and Socio-Emotional Endowments on Health Limits Work, Cont’d

E. Some College

Source: Heckman et al. (2016b).
Figure 32: The Effect of Cognitive and Socio-Emotional Endowments on Health Limits Work, Cont’d

F. Four-Year College

Source: Heckman et al. (2016b).
Understanding How Interventions Shape Family Life
Part IVB

James J. Heckman
University of Chicago

CeMMAP Masterclass
University College of London
June 23, 2016
Understanding How Interventions Shape Family Life
Supplementing and Bolstering Family Life
Attachment and Engagement:
Toward a Deeper Understanding of Parenting and Learning

- In both Perry and ABC (and many other interventions) a main channel of influence is on parent-child interactions.
- Supplementing family life.
- Scaffolding the child.
- Training the child—instilling values & motivation.
- Consistent with Aristotle’s notion of building good habits (virtue) through practice (*Nicomachean Ethics*, Book II).
- Enhanced *attachment* and *engagement* of parents.
- This has important implications for how we model family influence.
Mechanisms—producing effects

- Information
- Changing preferences of parents
- Parental response to child’s curiosity and interest induced by participation in the program
Figure 1: Parental Warmth, Perry Preschool

Note: This figure presents the densities –pooled and by treatment status– for a single factor summarizing a set of questions in the Perry questionnaire attempting to measure how much affection the child gets from the parent(s).
Figure 2: Parental Authoritarianism, Perry Preschool

Note: This figure presents the densities—pooled and by treatment status—for a single factor summarizing a set of questions in the Perry questionnaire attempting to measure how much affection the child gets from the parent(s).
Warm Parenting

Note: This plot densities by treatment status of a (factor) measure of parent-child warm relationship based on the Parental Attitude Research Instrument (PARI).
Figure 3: Parental Response to Perry Preschool Program After 1 year experience of treatment

Figure 4: Parental response to Perry Preschool Program after 1 year experience of treatment: Girls

Figure 5: Parental response to Perry Preschool Program after 1 year experience of treatment: Boys

Note: Eight measures of parental labor income are available from children’s ages 0 to 15. Six HOME scores are available from children’s ages 0 to 8. The plot displays the percentage of HOME score or parental income measures with a positive treatment-control mean difference.
Note: This plot densities by treatment status of a (factor) measure of parent authoritativeness based on the Parental Attitude Research Instrument (PARI).
Note: This plot densities by treatment status of a (factor) measure of parent-child democratic relationship based on the Parental Attitude Research Instrument (PARI).
## Table 1: Abecedarian Intervention, Attachment (Videotapes)

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<td></td>
<td></td>
<td>Males</td>
<td>Females</td>
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<td>Males</td>
<td>Females</td>
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<td>Mutual reading</td>
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<td>2.022</td>
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<td>0.040</td>
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<td>0.872</td>
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<td>178.659</td>
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</table>

Notes:
(a) Ctr. Mean denotes mean value for control group
(b) Diff. Means denotes the difference in the mean values between treatment and control groups
(c) Blk. p-value denotes the block p-value for the male block
(d) IPW P. Co. Co. denotes the inverse probability weighting correlation coefficient
(e) Gen. Diff. denotes the p-value for the mean values of the two genders being equal

### Table 2: Abecedarian Intervention, Parental Investment (HOME)

<table>
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<td>Organization of environment</td>
<td>30</td>
<td>5.238</td>
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<td>Stimulation of mature behavior</td>
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<td><strong>0.001</strong></td>
<td>9.000</td>
<td>1.000</td>
<td><strong>0.045</strong></td>
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</tbody>
</table>

**Notes:**
(a) Ctr. Mean denotes mean value for control group
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**Source:** Moon (2013).
Understanding the Components of the Treatment Effects
Understanding the Components of the Treatment Effects

- Construct principal components to measure
  - Non-cognitive or Character Skills
  - Parenting Behavior
- Measure cognitive skills through IQ tests
- Laspeyres decomposition of treatment effects later in life
  - Parenting behavior, character, and cognitive skills as mediators
Methodology

- \( D_i \) indicator of treatment for individual \( i \)
- \( Y_{i,k}^d, M_{i,k}^d, V_{i,k}^d \) denote outcomes, measures, and an unobserved term for outcome \( k \), in either treatment or control \( d \in \{0, 1\} \)
- Write counterfactual outcomes as

\[
\begin{align*}
Y_{i,k}^0 &= \beta_0^0 + \beta_k^0 M_{i,k}^0 + V_{i,k}^0 \\
Y_{i,k}^1 &= \beta_0^1 + \beta_k^0 M_{i,k}^1 + V_{i,k}^1
\end{align*}
\]  

(1)
• for $J = Y, M, V$, write outcomes, measures, and the observed term as

$$J_{i,k} = J^0_{i,k}(1 - D_i) + J^1_{i,k}D_i$$ (2)

• Write $k$th outcome as

$$Y_{i,k} = \beta^0_{0,k}(1 - D_i) + \beta^1_{0,k}D_i + [\beta^0_{k}M^0_{i,k}](1 - D_i) + [\beta^1_{k}M^1_{i,k}]D_i + V_{i,k}$$ (3)
Methodology (cont’d 2)

- Assume $\beta_k^0 = \beta_k^1 = \beta_k$
- Decompose the conditional mean as follows:

$$E[Y_{i,k} - Y_{i,k}^0 | D_i] = \underbrace{E[M_{i,k} - M_{i,k}^0]}_{\text{Mean } \Delta} \beta_k + \underbrace{(\beta_{0,k}^1 - \beta_{0,k}^0)}_{\text{Residual}}$$

(4)
Results for ABC
Early Skills as Mediators of Later Life Outcomes, Females and Males

Note: This plot is a graphical display of a Laspeyres decomposition of the outcomes in the y-axis in three different skills. Below the bar we display the mean difference in the outcome. Then, we decompose the length of these changes, which we normalize to one, in the experimentally induced treatment effects in skills. All the outcomes are at age 30. We measure skills based on extensive behavior and intelligence measures at age 15. Dark bars are significant under one-tailed tests.
Early Skills as Mediators of Later Life Outcomes, Females

Note: This plot is a graphical display of a Laspeyres decomposition of the outcomes in the y-axis in three different skills. Below the bar we display the mean difference in the outcome. Then, we decompose the length of these changes, which we normalize to one, in the experimentally induced treatment effects in skills. All the outcomes are at age 30. We measure skills based on extensive behavior and intelligence measures at age 15. Dark bars are significant under one-tailed tests.
**Early Skills and Parenting as Mediators of Later Life Outcomes, Females and Males**

*Note: This plot is a graphical display of a Laspeyres decomposition of the outcomes in the y-axis in three different skills. Below the bar we display the mean difference in the outcome. Then, we decompose the length of these changes, which we normalize to one, in the experimentally induced treatment effects in skills and parenting behavior. All the outcomes are at age 30. We measure character skills based on extensive behavior measures assessing openness to experience and conscientiousness at age 15. We measures cognitive skills through IQ. We measure parenting behavior as factors of extensive parenting batteries at age 5. Dark bars are significant under one-tailed tests.*
Early Skills and Parenting as Mediators of Later Life Outcomes, Females

Note: This plot is a graphical display of a Laspeyres decomposition of the outcomes in the y-axis in three different skills. Below the bar we display the mean difference in the outcome. Then, we decompose the length of these changes, which we normalize to one, in the experimentally induced treatment effects in skills and parenting behavior. All the outcomes are at age 30. We measure character skills based on extensive behavior measures assessing openness to experience and conscientiousness at age 15. We measure cognitive skills through IQ. We measure parenting behavior as factors of extensive parenting batteries at age 5. Dark bars are significant under one-tailed tests.
Results for Perry
Understanding Interventions

Note: This plot is a graphical display of a Laspeyres decomposition of the outcomes in the y-axis in three different measures of parenting behavior. Below the bar we display the mean difference in the outcome. Then, we decompose the length of these changes, which we normalize to one, in the experimentally induced treatment effects in parenting behavior. We measure the outcomes as factors of extensive behavior batteries at ages 3 to 14. We measure parenting behavior as factors of extensive parenting batteries at age 5. Dark bars are significant under one-tailed tests.
Early Skills as Mediators of Later Life Outcomes, Females and Males

Note: This plot is a graphical display of a Laspeyres decomposition of the outcomes in the y-axis in three different skills. Below the bar we display the mean difference in the outcome. Then, we decompose the length of these changes, which we normalize to one, in the experimentally induced treatment effects in skills. All the outcomes are at age 30. We measure skills based on extensive behavior and intelligence measures at ages 3 to 14. Dark bars are significant under one-tailed tests.
Early Skills and Parenting as Mediators of Later Life Outcomes, Females and Males

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Understanding the Mechanisms Through Which an Influential Early Childhood Program Boosted Adult Outcomes

by Heckman, Pinto, and Savelyev

Part IVC

James J. Heckman
University of Chicago

CeMMAP Masterclass
University College of London
June 23rd, 2016
Based on:

“Understanding the Mechanisms Through Which an Influential Early Childhood Program Boosted Adult Outcomes”
by James Heckman, Rodrigo Pinto, and Peter Savelyev
(American Economic Review, 2013)
Experiments are widely used in economics.

Many studies report “treatment effects” of specific interventions.

Few studies go beyond reporting treatment effects to examine the mechanisms—the “production functions”—producing the treatment effects. (Although several papers published each year talk about going into the “black box” of experiments.)

Understanding these mechanisms facilitates comparison of the findings from a particular study with those of other studies.

In particular, understanding the mechanisms producing experimental effects is helpful in designing effective social policies that can be applied to a wider array of environments and target populations, different from the environments and populations studied in any particular experiment.

Translate treatment effects into $\theta$, effects on the fundamental factors underlying all treatment effects and programs.
This paper develops and applies methods for investigating the factors producing the treatment effects obtained from an influential early childhood program.

Focusing on the factors producing the treatment effects instead of just the treatment effects facilitates comparison of the findings from a variety of literatures on the determinants of skill formation in early childhood.

The goal is to understand and compare the sources of treatment effects across diverse studies.
The methods developed in this paper are closely related to path analysis (Wright, 1934), innovation accounting and final forms of dynamic stochastic econometric models (Klein and Goldberger, 1955 and Theil and Boot, 1962). Statisticians and computer scientists working on “causal models” are recently rediscovering these methods under the rubric “mediation analysis” (e.g., Pearl, 2011).

All methods considered today have nonparametric counterparts, but because of the small size of our sample, use a simple linear-in-parameters setup to obtain estimates.
Plan of This Part of the Talk

1. Discuss the experiment analyzed and show its treatment effects.
3. Present empirical estimates.
2. Econometric Analysis of Production Functions

- Cognitive traits (IQ) surged, then faded because of catch-up.
- Noncognitive traits also surged but did not decline – treatment group members had stable improvements over the life cycle.
- Can we establish that the Perry treatment effects are caused by boosts in noncognitive skills?
- Which noncognitive skills?
- How to interpret the sources of the Perry treatment effects? To relate it to other experiments and to family influence studies?
• Challenges of the Perry Study
  i Experiment induces exogenous changes in *measured* traits.
  ii May also induce exogenous changes in *unmeasured* traits.
  iii The exogenous changes in the measured and the unmeasured traits may be correlated.

• In addition:
  iv Small sample size.
  v Multiple measures of noncognitive traits (easy to exhaust degrees of freedom): need low dimensional interpretable summary measures of traits.
  vi Need criteria for picking summary measures.
  vii Psychological measures are riddled with error and need to account for this.
Human Capabilities

- To organize our thinking, we use the notion of capabilities that (along with incentives in situations) generate a variety of outcomes.
- An agent at age $t$ is characterized by a vector of capabilities:

$$\theta_t = (\theta_{C,t}, \theta_{N,t}, \theta_{H,t})$$

- $\theta_{C,t}$: vector of cognitive abilities (e.g., IQ) at age $t$.
- $\theta_{N,t}$: vector of noncognitive abilities at age $t$ (e.g., patience, self control, temperament, risk aversion, and neuroticism).
- $\theta_{H,t}$: vector of health stocks for mental and physical health at age $t$. 
Model of child outcomes

- The outcome from activity $j$ at age $t$ is $Y_{j,t}$, where

$$Y_{j,t} = \psi_j \left( \theta_{C,t}, \theta_{N,t}, \theta_{H,t}, e_{j,t} \right) \theta_t, \quad j \in \{1, \ldots, J_t\} \quad (1)$$

where $e_{j,t}$ is effort devoted to activity $j$ at time $t$ where the effort supply function depends on rewards and endowments:

$$e_{j,t} = \delta_j (R_{j,t}, A_t) \quad (2)$$

where $R_{j,t}$ is the reward per unit effort in activity $j$ and $A_t$ represents other determinants of effort that might include some or all of the components of $\theta_t$. 
Capability Formation Process

• The technology of capability formation (Cunha and Heckman, 2007):

\[ \theta_{t+1} = f_t(\theta_t, I_t, \theta_{P,t}). \] 

• \( \theta_{t+1} \): Stock of period \( t + 1 \) capabilities.
• \( \theta_t \): Stock of period \( t \) capabilities.
• \( I_t \): Investments: Perry intervention; Parental influence, etc.
• \( \theta_{P,t} \): Parental environments.
• \( \theta_0 \): Vector of initial endowments.
Integrating Family Intervention Studies With Family Influence Studies

- Seek to understand how interventions supplement, complement, or substitute for family investments.
- Technology of skill formation allows economists to integrate diverse studies through their effects on $\theta_t$.
  - Can model interaction of parental investment with governmental investments: components may be perfect substitutes or not.
  - Identify different technologies (public and private) that produce $\theta_t$. 
Examples:

- $I_t^G$: Government investment.
- $I_t^F$: Private (family) investment.
- Government technology: 
  \[ f^G(\theta_t, \theta_t^P, I_t^G, I_t^F, \theta_{P,t}) \].
- Family technology: 
  \[ f^F(\theta_t, \theta_t^P, I_t^F, I_t^G, \theta_{P,t}) \].

One Specification:

- $\theta_{t+1} = f^G(\theta_t, \theta_t^P, I_t^G, I_t^P, \theta_{P,t}) + f^F(\theta_t, \theta_t^P, I_t^P, I_t^G, \theta_{P,t})$.
- Family chooses inputs to minimize the cost of achieving a given level of capabilities.
An Alternative Specification:

- Families may have multiple private technologies, as well as government technology, and choose least cost envelope of technologies.
- Can establish the channels through which government (external) investment promotes capabilities.
- Can determine the capabilities that each technology produces.
Stochastic Specifications

- Outcomes

\[ Y_{j,t} = \psi_j (\theta_t, e_t, \varepsilon_{j,t}), \quad t \in \{1, \ldots, T\}, \quad j \in \{1, \ldots, J_t\}. \tag{4} \]

- Production Technology:

\[ \theta_{t+1} = f_t (\theta_t, I_t, \theta_{P,t}, \eta_t) \tag{5} \]

\[ t \in \{1, 2, \ldots, T\}. \]
Does the Persistent Boost in Measured Noncognitive Skills Explain the Favorable Perry Results?

- Consider a case with a scalar input:

\[
Y_j \uparrow \quad \text{when} \quad I \uparrow
\]

(outcome)

\[
\theta_M \uparrow \quad \text{when} \quad I \uparrow
\]

(measured traits)

\[\implies \theta_M \uparrow \quad \Rightarrow \quad Y_j \uparrow \quad ?\]

- Obvious problem: unmeasured traits \(\theta_U\).
- If \(\theta_U \uparrow\) when \(I \uparrow\) and \(Y_j = \psi(\theta_M, \theta_U)\), both inputs could be increased by \(I \uparrow\).
• We need to account for boosts in unmeasured traits to make any convincing causal story that
\[ \theta_M \uparrow \iff Y \uparrow. \]

• The experiment is a “dose” operating at multiple margins.

• It does not manipulate \( \theta_M \) holding \( \theta_U \) fixed.

• The experimental evidence can only be suggestive on the question of the sources of the treatment effects.

• Assuming \( \Delta \theta_M \perp \perp \Delta \theta_U \) obviously avoids the problem
\( (\Delta \theta_M = \theta_{M,1} - \theta_{M,0}; \ \Delta \theta_U = \Delta \theta_{U,1} - \Delta \theta_{U,0}). \)

• With experiment we can test this assumption under autonomy.
An Econometric Framework for Investigating the Causes of Effects

- \( D \) denotes treatment assignment.
- \( D = 1 \) if an agent is treated and \( D = 0 \) otherwise.
- \( Y_1 \) and \( Y_0 \) are the counterfactual outcome when \( D \) is fixed at “1” and “0” respectively.
- Observed outcome is

\[
Y = D Y_1 + (1 - D) Y_0.
\]  

(6)

- Assume no social interactions. (Alternatively, since we have data from one site, any treatment effects are inclusive of social interactions.)
Notation

- $Y_d$: Outcome $Y$ when treatment status is \textit{fixed} at $d \in \{0, 1\}$.
- $X$: Vector of pre-program variables.
- $\theta_d = (\theta^j_d : j \in \mathcal{J})$: Vector of skills when treatment is \textit{fixed} at $d$.
- $\mathcal{J}$: Index set for skills.
- $\theta_0$ and $\theta_1$: Potential skills of the untreated and the treated.
- $\theta = D\theta_1 + (1 - D)\theta_0$
- The intervention is an investment.
Outcome Equation

- Linear model:
  \[ Y_d = \kappa_d + \alpha_d \theta_d + \beta_d X + \tilde{\epsilon}_d, \quad d \in \{0, 1\}. \] (7)

- Trivially, also a log linear model (Cobb-Douglas technologies).

- \( \alpha_d \) and \( \beta_d \): \(|\mathcal{J}|\)-dimensional and \(|X|\)-dimensional vectors of parameters.

- \((\theta_d, X) \perp \perp \tilde{\epsilon}_d, E(\tilde{\epsilon}_d) = 0\)
- \( J_p \subseteq J \): index set of measured skills.
- Rewrite equation (7):

\[
Y_d = \kappa_d + \sum_{j \in J} \alpha^j_d \theta^j_d + \beta_d X + \tilde{\epsilon}_d
\]

\[
= \kappa_d + \sum_{j \in J_p} \alpha^j_d \theta^j_d + \sum_{j \in J \setminus J_p} \alpha^j_d \theta^j_d + \beta_d X + \tilde{\epsilon}_d
\]

\[
= \tau_d + \sum_{j \in J_p} \alpha^j_d \theta^j_d + \beta_d X + \epsilon_d \quad d \in \{0, 1\} \tag{8}
\]

- \( \tau_d = \kappa_d + \sum_{j \in J \setminus J_p} \alpha^j_d E(\theta^j_d) \)
- \( \epsilon_d = \tilde{\epsilon}_d + \sum_{j \in J \setminus J_p} \alpha^j_d (\theta^j_d - E(\theta^j_d)) \)
- Without any loss of generality, assume \( \tilde{\epsilon}_1 \overset{\text{dist}}{=} \tilde{\epsilon}_0 \).
Structural Invariance (Autonomy)

- If treatment affects skills, but not the map between skills and outcomes, \( \alpha_1^j = \alpha_0^j; \ j \in \mathcal{J} \) and \( \beta_1 = \beta_0 \).
- This assumption simplifies the interpretation of how the program operates.
- Under exogeneity, \( (\theta_M,d \perp \perp \theta_U,d) \mid X, \ d \in \{0,1\} \), it is not necessary to impose these assumptions and can identify separate \( \alpha_1 \) and \( \alpha_0 \).
• Alternatively, maintaining autonomy allows for a test of one of the exogeneity assumptions.

• If $\theta_{M,0} \perp \perp \theta_{U,0}\mid X$ and $\alpha_1 = \alpha_0, \beta_1 = \beta_0$

can test if the experimentally-induced increments in unmeasured skills are independent of the experimentally induced increments in measured skills.

• Thus, can test if $(\theta_{M,1} - \theta_{M,0}) \perp \perp (\theta_{U,1} - \theta_{U,0})\mid X$ i.e., $\theta_{M,0} \perp \perp \theta_{U,1}$.

• Test

\[ \text{plim} \hat{\alpha}_1 = \text{plim} \hat{\alpha}_0; \text{plim} \hat{\beta}_1 = \text{plim} \hat{\beta}_0. \]  

(9)

• Heckman et al. (2013) do not reject this assumption.

• Can reverse the roles of $\theta_{M,1}$ and $\theta_{U,1}$ with $\theta_{M,0}$ and $\theta_{U,0}$.

• We can interpret the test as:

1. As a test of autonomy given full exogeneity.
2. Or a test of independence in the increments given autonomy.
3. Relaxing both requires more instruments.
• Simplified notation:

\[ Y_d = \tau_d + \sum_{j \in J_p} \alpha^j \theta^j + \beta X + \epsilon_d, \quad d \in \{0, 1\}. \quad (10) \]

• (6) rewritten in Switching Regression form:

\[
Y = D (\tau_1 + \sum_{j \in J_p} \alpha^j \theta^{j_1} + \beta X + \epsilon_1) + (1 - D) (\tau_0 + \sum_{j \in J_p} \alpha^j \theta^{j_0} + \beta X + \epsilon_0)
\]

\[
= \tau_0 + \tau D + \sum_{j \in J_p} \alpha^j \theta^{j_1} + \beta X + \epsilon.
\]

\( (11) \)

• \( \tau = \tau_1 - \tau_0 \): the contribution of unmeasured variables to the mean treatment effects.

• \( \epsilon = D \epsilon_1 + (1 - D) \epsilon_0 \): zero-mean error term.

• \( \theta^j = D \theta^{j_1} + (1 - D) \theta^{j_0}, \; j \in J_p. \)
• Decomposing Treatment Effects Under Autonomy and Independence of the Increments of Measured and Unmeasured Skills:

\[ E(Y_1 - Y_0 | X, \theta) = (\tau_1 - \tau_0) + \sum_{j \in J_p} \alpha^j E(\theta^j_1 - \theta^j_0). \]

(12)
Producing Low-Dimensional Summaries of Skills

- Summarize the numerous available psychological and behavioral measures using factor models.
- Measurement system is assumed to be the same across treatments and controls although $\theta_1$ can differ from $\theta_0$.
- Can test this assumption
- Do not reject
The Measurement System

- Index set for measures associated with factor $j \in J_p$: $M^j$.
- Measures for factor $j$: $M^j_{m^j, d}$, $m^j \in M^j$, $d \in \{0, 1\}$.
- $\theta_d$: vector of factors associated with the measured skills.
- The measurement system is based on dedicated measures:

$$\text{Measures} : M^j_{m^j, d} = \nu^j_{m^j} + \varphi^j_{m^j}\theta^j_d + \eta^j_{m^j}.$$  

(13)

$\nu^j_{m^j}$, $\varphi^j_{m^j}\theta^j_d$, and $\eta^j_{m^j}$ represent measurement error.
• Issues:
  a. Selecting the dimension of the summary measures.
  b. Picking the subset of dedicated measurements among all measures.
Table 1: Cognitive and Noncognitive Factors and Their Measures

<table>
<thead>
<tr>
<th>Cognition Measures (a)</th>
<th>Age</th>
<th>Externalizing Behavior Measures (a)</th>
<th>Age (b)</th>
<th>Academic Motivation Measures (a)</th>
<th>Age (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stanford-Binet IQ</td>
<td>7</td>
<td>Disrupts classroom procedures</td>
<td>7–9</td>
<td>Shows initiative</td>
<td>7–9</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>Swears or uses obscene words</td>
<td>7–9</td>
<td>Alert and interested in school work</td>
<td>7–9</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>Steals</td>
<td>7–9</td>
<td>Hesitant to try, or gives up easily</td>
<td>7–9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Lying or cheating</td>
<td>7–9</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Influences others toward troublemaking</td>
<td>7–9</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Aggressive toward peers</td>
<td>7–9</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Teases or provokes students</td>
<td>7–9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cronbach's alpha (c), males</td>
<td>0.838</td>
<td>Cronbach's alpha, males</td>
<td>0.906</td>
<td>Cronbach's alpha, males</td>
<td>0.901</td>
</tr>
<tr>
<td>Cronbach's alpha, females</td>
<td>0.913</td>
<td>Cronbach's alpha, females</td>
<td>0.916</td>
<td>Cronbach's alpha, females</td>
<td>0.896</td>
</tr>
</tbody>
</table>

Note: (a) Age measures, (c) Cronbach's alpha.
Characterizing the Measurement System

- Dedicated measures are informative on only one factor.

\[ M_{m_j,d}^j = \nu_{m_j}^j + \varphi_{m_j}^j \theta_d^j + \eta_{m_j}^j \]  

\[ j \in \mathcal{J}_p, \ m_j^i \in \mathcal{M}_j \]  

Factor Means: \( E[\theta_d^j] = \mu_d^j, \ j \in \mathcal{J}_p \)  

Factor Covariance: \( \text{Var}[\theta_d] = \Sigma_{\theta_d}, \ d \in \{0, 1\} \).  

- The covariance matrix not restricted to be diagonal.
- The \( \eta_{m_j}^j \) uncorrelated with \( \eta_{m_k}^k, \ k \neq j \) all \( j, k \in \mathcal{J}_p \).
- \( X \) left implicit.
Appendices Directory

The Outcome Equation (Under Autonomy)

Outcomes: \( Y_d = \tau_d + \alpha \theta_d + \epsilon_d \). \hspace{1cm} (17)

- \( \alpha = (\alpha^j : j \in J_p) \): outcome factor loadings.
- \( E(\epsilon_d) = 0 \quad E(\eta^j_{mi}) = 0 \).
- \( (\epsilon_d, \eta^j_{mi}) \perp \theta_d, j \in J_p, d \in \{0, 1\} \).
Normalizations: Setting Scale and Location (of Factors)

- Set location of each factor off of “first” measure within each set of dedicated measures: \( \nu^j_1 = 0, \ j \in \mathcal{J}_n \).
- Set the scale of each factor off of “first” measure within each set of dedicated measures: \( \varphi^j_1 = 1, \ j \in \mathcal{J}_n \).
- Decomposition is invariant to the choice of normalizing (“first”) measure as long as the measure has a non-zero factor loading.
- Under autonomy, decomposition invariant to affine transformations of the measures (excluding transformations that zero out factors).
Identification of the Factor Model

- Identification: established in four steps.
  1. First, identify the means of the factors, $\mu_d^j$.
  2. Second, identify the measurement factor loadings, $\varphi_{jm}^j$, variances $\text{Var}(\eta_{mj}^j)$ of the measurement system, and the factor covariance structure $\Sigma_{\theta_d}$.
  3. Third, use the parameters identified from the first and second steps to secure identification of the measurement intercepts $\nu_{mj}^j$.
  4. Fourth, use the parameters identified in the first three steps to identify the factor loadings $\alpha$ and intercept $\tau_d$ of the outcome equation.
  5. The factor model is identified by measurements, not by outcomes. Factors not picked to predict outcomes. We test if the factors so chosen predict outcomes.
1 **Factor Means**

- Obtain $\mu^j_1$ and $\mu^j_0$ from the expectation of the first measure for treatment and control groups as 
  $$E(M^j_{1,d}) = \mu^j_d, \; j \in J_p, \; d \in \{0, 1\}.$$

2 **Covariance of measurements: $\Sigma_M$.**

- From $\Sigma_M$ can identify:
  1. The factor loadings of the measurement system 
     $$\varphi^j_{m^j}, \; j \in J_p$$
  2. The variances of the measurement error terms, 
     $$\text{Var} \; \eta^j_{m^j}, \; j \in J_p$$
  3. The factor covariance matrix, $\Sigma_{\theta_d}$.

- Can identify $\varphi^j_{m^j,d}, \; d \in \{0, 1\}$.

- Test if $H_0: \varphi^j_{m^j,1} = \varphi^j_{m^j,0}, \; m^j \in M^j \setminus \{1\}, \; j \in J_p$.

- Do not reject.
3 Measurement Intercepts

- Means of the measurements, \( E(M^j_{m^j,d}) = \nu^j_{m^j} + \varphi^j_{m^j} \mu^j_d \) identified from previous arguments.

- \( \nu^j_{m^j} \) identified, \( m^j \in M^j \setminus \{1\}, j \in J_p \).

- Equality of the intercepts (\( \nu^j_{m^j} \)) between treatment and control groups guarantees model consistency.

- Treatment effects on measures operate only through the \( \theta \).
  \( E(M^j_{m^j,1}) - E(M^j_{m^j,0}) = \varphi^j_{m^j} (\mu^j_1 - \mu^j_0) \).

- Test if \( H_0 : \nu^j_{m^j,1} = \nu^j_{m^j,0} \) for all \( m^j \in M^j \setminus \{1\}, j \in J_p \).

- Do not reject.
4 Outcome Equation

- Stack the covariances of outcome $Y_d$ across the first measure of each skill $j \in \mathcal{J}_p$

\[
\text{Cov}(Y_d, M_{1,d}) = \Sigma_{\theta_d} \alpha.
\]

- Observed

- Produced by preceding analysis

- $\alpha$ identified if $\det(\Sigma_{\theta_d}) \neq 0$.

- $\alpha$ can depend on $d \in \{0, 1\}$: $\text{Cov}(Y_d, M_{1,d}) = \Sigma_{\theta_d} \alpha_d$

- $d \in \{0, 1\}$.

- Can test if $H_0 : \alpha^j_1 = \alpha^j_0, \forall j \in \mathcal{J}_p$.

- Do not reject.
• This is consistent with the hypothesis of autonomy and that the hypothesis that \textit{increments} in unmeasured skills are uncorrelated with \textit{increments} in measured skills i.e.

\[ (\theta_{M,1} - \theta_{M,0}) \perp (\theta_{U,1} - \theta_{U,1})|X. \] \hspace{1cm} (18)

• Clearly if we relax autonomy and adopt full independence for controls and treatments we can identify \( \alpha_d \)
Link to Estimation Procedure
Testing the Validity of the Derived System: Testing the Overidentifying Assumptions

- Model imposes many restrictions analogous to separability restrictions in demand analysis.
- We test the validity of the derived factor structure.
- Test if the excluded measures have predictive power—conditional on the extracted factors.
Model Specification Tests

General notation:

\[ Y = \tau_0 + \tau_1 D + \alpha \theta + \beta X + \epsilon \]  \hspace{1cm} (19)
\[ M = \nu + \varphi \theta + \eta \]  \hspace{1cm} (20)

\[ \text{Dim}(M) \gg \text{Dim}(\theta) \text{ (Satisfies Ledermann bound).} \]

- Test I: **Conditional on extracted factors**, do unused components of \( M \) differ across \( d = 0 \) and \( d = 1 \) states?
- Test II: **Conditional on extracted factors**, do unused components of \( M \) predict \( Y \)?
- Evidence from both types of tests support the low-dimensional specification of equations (14)–(17) derived from applying EFA.
Invariance of the Decomposition to Affine Transformations of the Measures

- The decomposition under autonomy assumes that the outcome system is autonomous: \( \alpha_0 = \alpha_1 \), and \( \beta_0 = \beta_1 \).
- Suppose that \( \alpha_0 \neq \alpha_1 \). To simplify the argument, assume that \( \beta_0 = \beta_1 \).
- In this case

\[
E(Y_1 - Y_0) = E(\alpha'_1 \theta_1 - \alpha'_0 \theta_0).
\]
In the general case, the decomposition is **not** unique, but the part of it we report **is** unique.

Define $\Delta \alpha = \alpha_1 - \alpha_0$,

$$E(Y_1 - Y_0) = \underbrace{\alpha'_0 E(\theta_1 - \theta_0)}_{\text{invariant to affine transformations of measures}} + \underbrace{(\Delta \alpha)' E(\theta_1)}_{\text{non-invariant to affine transformations of measures}}$$

$$= \underbrace{\alpha'_1 E(\theta_1 - \theta_0)}_{\text{invariant to affine transformations of measures}} - \underbrace{(\Delta \alpha) E(\theta_0)}_{\text{non-invariant to affine transformations of measures}}.$$
• For any $\alpha^*$ that is an affine transformation of $(\alpha_0, \alpha_1)$

$$E(Y_1 - Y_0) = (\alpha^*)E(\theta_1 - \theta_0) + (\alpha_1 - \alpha^*)E(\theta_1) - (\alpha_0 - \alpha^*)E(\theta_0).$$

- invariant to affine transformations
- non-invariant to affine transformations
3. The Effect of Treatment on Traits and the Sources of Treatment Effects
Figure 1: Kernel Densities of Factor Scores

(a) Cognition, Males

\[ p = .683 \]

(b) Cognition, Females

\[ p = .095 \]

Notes: Probability density functions of Bartlett (1937) factor scores are shown. Densities are computed based on a normal kernel. Numbers above the charts are one-sided \( p \)-values testing the equality of factor score means for the treatment and control groups. Higher noncognitive scores correspond to more socially desirable behaviors like less aggression and greater interest in schooling.
Figure 1: Kernel Densities of Factor Scores

(c) Externalizing Behavior, Males

\[ p = .038 \]

(d) Externalizing Behavior, Females

\[ p = .006 \]

Notes: Probability density functions of Bartlett (1937) factor scores are shown. Densities are computed based on a normal kernel. Numbers above the charts are one-sided \( p \)-values testing the equality of factor score means for the treatment and control groups. Higher noncognitive scores correspond to more socially desirable behaviors like less aggression and greater interest in schooling.
Figure 1: Kernel Densities of Factor Scores

(e) Academic Motivation, Males  \[ p = .183 \]

(f) Academic Motivation, Females  \[ p = .048 \]

Notes: Probability density functions of Bartlett (1937) factor scores are shown. Densities are computed based on a normal kernel. Numbers above the charts are one-sided \( p \)-values testing the equality of factor score means for the treatment and control groups. Higher noncognitive scores correspond to more socially desirable behaviors like less aggression and greater interest in schooling.
Figure 2: Decompositions of Treatment Effects on Outcomes, Males

Notes: 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. “CAT total” denotes California Achievement Test total score normalized to control mean zero and variance of one. Asterisks denote statistical significance: * – 10 percent level; ** – 5 percent level; *** – 1 percent level. Monthly income is adjusted to thousands of year-2006 dollars using annual national CPI.
Figure 3: Decompositions of Treatment Effects on Outcomes, Females

Notes: 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 in each outcome. “CAT total” denotes California Achievement Test total score normalized to control mean zero and variance of one. Asterisks denote statistical significance: * – 10 percent level; ** – 5 percent level; *** – 1 percent level.
Link to More Efficient Estimates
Conclusions

- Develop and apply methods for estimating the sources of treatment effects in social experiments (i.e., identifying production functions).
- The framework allows us to integrate treatment effects into structural economic models of the life cycle skill development and expression.
- Using experimental variation coupled with an econometric model, we estimate the role of enhancements in Cognition, Externalizing Behavior, and Academic Motivation in producing the Perry treatment effects.
- Persistent changes in noncognitive skills play a substantial role in producing the success of the Perry program.
• Especially strong is the reduction in Externalizing Behavior that explains the substantial effects of Perry in reducing crime.

• Cannot rule out the possibility that changes in cognitive skills (IQ) while transient had persistent effects on the noncognitive skills.

• Need to estimate the transient dynamics of the model. This is a challenge in a sample of the size of Perry. (Estimates support this, see Cunha et. al, 2007.)

• Framework for integrating findings across interventions and observational studies.
Appendices Directory

- Appendix 1: Identification and Parameter Restrictions
- Appendix 2: Tests
- Appendix 3: Invariance of the Decompositions to Linear Transformations of Measurements
- Appendix 4: Factor Regression
- Appendix 5: Correcting the Factor Regression Model for Measurement Errors
- Appendix 6: Separability Tests (Tests of Model Specification)
- Appendix 7: Identifying The Factor Structure
- Appendix 8: Nonlinear Factor Analysis
- Appendix 9: Identifying the Nonlinear Technology using Dynamic Factor Models
Appendix 1: Identification and Parameter Restrictions
Skills are latent variables not observed directly but rather measured with error by multiple proxies.

We use a factor model to estimate latent skills.

Notationally, let the index set for measures associated with factor \( j \in J_p \) be \( M^j \).

We denote the measures for factor \( j \) by \( M^j_{m^j, d} \), where \( m^j \in M^j \), \( d \in \{0, 1\} \).

Each factor \( j \) may be associated with a different number of measures.

Henceforward we denote the vector of factors associated with the measured variables \( (\theta^j_d : j \in J_p), d \in \{0, 1\} \) by \( \Theta_d \).
We are now able to specify our model:

The First Measure: \( M_{1,d}^j = \nu_1^j + \varphi_1^j \theta_d^j + \eta_1^j, \quad \forall j \in J_p \) \hfill (21)

Remaining Measures: \( M_{m^j,d}^j = \nu_{m^j}^j + \varphi_{m^j}^j \theta_d^j + \eta_{m^j}^j, \quad \forall j \in J_p \) \hfill (22)

Outcomes: \( Y_d = \tau_d + \alpha \theta_d + \epsilon_d \) \hfill (23)

Factor Means: \( E[\theta_d^j] = \mu_d^j, \quad \forall j \in J_p \) \hfill (24)

Factor Covariance: \( \text{Var}[\theta_d] = \Sigma_{\theta_d} \), \hfill (25)
• \( d \in \{0, 1\}, \ m^j \in \mathcal{M}^j, \) and \( j \in \mathcal{J}_p. \)

• measurement system is based on dedicated measures

• Parameters \( \nu^j_{mj} \) are measure-specific intercept terms.

• Parameters \( \varphi^j_{mj} \), and factor loadings of the measurement system.

• Parameter \( \tau_d \) is an outcome-specific intercept term and parameters \( \alpha = (\alpha^j : j \in \mathcal{J}_p) \) are the outcome factor loadings.

• \( \epsilon_d \) and \( \eta^j_{mj} \) are zero-mean error terms independent of \( \theta_d, \ d \in 0, 1. \)

• Equations (24) and (25) define factor means and factor covariances.
Model Identification

- **Normalization:**
  - We set the location by fixing the intercepts of the first measure of each skill to zero,
  - i.e. $\nu_1^j = 0$, $\forall j \in J_p$,
  - and we set the scale by fixing the factor loadings of the first measure of each skill to one, i.e. $\varphi_1^j = 1$, $\forall j \in J_p$.
  - Our outcome decomposition is invariant to the choice of the first measure.
  - In addition, our decomposition is invariant under any linear transformations of measures.
• Our model identification procedure is in four steps.
• First, we identify the factor means $\mu_d^j$.
• Second, we identify the measurement factor loadings $\varphi_{m_i}^j$, the variances $\text{Var}(\eta_{m_i}^j)$ of the measurement system, and the factor covariance structure ($\Sigma_{\theta_d}$).
• Third, we identify the measure system intercepts $\nu_{m_i}^j$.
• Finally, we identify the factor loadings $\alpha$ and intercept $\tau_d$ of the outcome equation.
Factor Means

- Obtain $\mu_1^j$ and $\mu_0^j$ from the expectation of the first measure for treatment and controls groups as

$$E(M_{1,d}^j) = \mu_d^j, \quad \forall \ j \in J_p, \ d \in \{0, 1\}. \quad (26)$$
Measurement Loadings

\[ \phi_{mj}^j = \frac{\text{Cov}(M_{mj}, M_{(mj)'}, d)}{\text{Cov}(M_{1,d}, M_{(mj)'}, d)} \quad \text{if} \quad \text{Cov}(M_{1,d}, M_{(mj)'}, d) \neq 0, \quad (27) \]

\[ \text{Var}(\theta_{jd}) = \frac{\text{Cov}(M_{1,d}, M_{mj}', d) - \phi_{mj}^j}{\phi_{mj}^j} \quad \text{if} \quad \phi_{mj}^j \neq 0, \quad (28) \]

\[ \text{Var}(\eta_{mj}) = \text{Var}(M_{mj}, d) - [\phi_{mj}^j]^2 \cdot \text{Var}(\theta_{jd}), \quad (29) \]

\[ \text{Cov}(M_{1,d}, M_{1,d}') = \text{Cov}(\theta_{d}, \theta_{d}') \quad \forall j, j' \in J_p; j' \neq j. \quad (30) \]

- Notice that in Equation (27) \( \phi_{mj}^j \) might depend on \( d \in \{0, 1\} \), that is \( \phi_{mj}^j, d \).
- In this case we must normalize \( \phi_{1,1}^j = \phi_{1,0}^j \).
- We test the hypothesis \( H_0 : \phi_{mj,1}^j = \phi_{mj,0}^j, m_j \neq 1 \), and we do not reject (Table 4).
Measurement Intercepts

• Factor loadings $\phi_{m^j}^j$, $\forall m^j \in \mathcal{M}^j$ and factor means $\mu_d^j$ such that $j \in \mathcal{J}_p$, $d \in \{0, 1\}$ are already identified.

• Therefore, we can write:

$$\nu_{m^j}^j = E(M^j_{m^j,d}) - \phi_{m^j}^j \mu_d^j$$  \hspace{1cm} (31)

• To identify $\nu_{m^j}^j$, $\forall m^j \in \mathcal{M}^j \setminus \{1\}$, $j \in \mathcal{J}_p$, we assume that the intercept $\nu_{m^j}^j$ for each component of each measurement equation does not depend on $d$.

• This assumption is necessary for model consistency.

• If $\nu_{m^j}^j$ does not depend on $d$, then the treatment effect on measures, that is, $E(M^j_{m^j,1}) - E(M^j_{m^j,0})$, must operate through treatment effects on factor means, i.e. $\mu_1^j - \mu_0^j$. 

Heckman The Economics/Econometrics
• Model identification only requires intercept equality on the first measure of each factor across treatment states.

• We perform a robustness check by testing the equality of intercepts $H_0 : \nu^j_{m^j,1} = \nu^j_{m^j,0}$ for all measures except the first one. We cannot reject the equality of intercepts for any factor at the 10% level (Table 4).
• Equation (32) gives the covariance between an outcome \( Y_d \) and a first measure \( M^{i}_{1,d} \):

\[
\text{Cov}(Y_d, M^i_{1,d}) = \left( \alpha^i \text{Var}(\theta^i_d) + \sum_{j' \in \mathcal{J}_p \setminus \{j\}} \alpha^{j'} \text{Cov}(\theta^i_d, \theta^{j'}_d) \right). \tag{32}
\]

• Equation (32) can be represented in a more concise form.

• For notational brevity, we can stack the covariance of outcome \( Y_d \) across the first measures of skills \( j \in \mathcal{J}_p \) to obtain

\[
\text{Cov}(Y_d, M_{1,d}) = [\text{Cov}(Y_d, M^i_{1,d}) : j \in \mathcal{J}_p].
\]
Thus, we can represent the Equation (32) for all factors $j \in J_p$ by $\text{Cov}(Y_d, M_{1,d}) = \sum_{\theta_d} \alpha$. Notice that $\sum_{\theta_d}$ is already identified (step 2).

Therefore, $\alpha$ is identified whenever $\det(\sum_{\theta_d}) \neq 0$. Using the outcome equation we can allow the factor loadings of the outcome equation to depend on $d \in \{0, 1\}$, as they can be identified through $\text{Cov}(Y_d, M_{1,d}) = \sum_{\theta_d} \alpha_d$.

We test if $H_0 : \alpha_1 = \alpha_0 \ \forall \ m^j \in M^j, \ j \in J_p$, and we do not reject these hypotheses.
Appendix 2: Tests
Table 2: Some Selected Program Treatment Effects (Males)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Age</th>
<th>Effect</th>
<th>Effect Size</th>
<th>p-value</th>
<th>Control Group</th>
<th>Treatment Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Males</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAT total at age 14, end of grade 8</td>
<td>14</td>
<td>0.566</td>
<td>0.652</td>
<td>(0.060)</td>
<td>0.000</td>
<td>0.566</td>
</tr>
<tr>
<td># of misdemeanor arrests, age 27</td>
<td>27</td>
<td>-1.21</td>
<td>-0.363</td>
<td>(0.036)</td>
<td>3.03</td>
<td>1.82</td>
</tr>
<tr>
<td># of felony arrests, age 27</td>
<td>27</td>
<td>-1.12</td>
<td>-0.324</td>
<td>(0.101)</td>
<td>2.33</td>
<td>1.21</td>
</tr>
<tr>
<td># of adult arrests (misd.+fel.), age 27</td>
<td>27</td>
<td>-2.33</td>
<td>-0.402</td>
<td>(0.024)</td>
<td>5.36</td>
<td>3.03</td>
</tr>
<tr>
<td>Monthly income, age 27</td>
<td>27</td>
<td>0.876</td>
<td>0.607</td>
<td>(0.018)</td>
<td>1.43</td>
<td>2.31</td>
</tr>
<tr>
<td>Use tobacco, age 27</td>
<td>27</td>
<td>-0.119</td>
<td>-0.236</td>
<td>(0.093)</td>
<td>0.538</td>
<td>0.419</td>
</tr>
<tr>
<td># of misdemeanor arrests, age 40</td>
<td>40</td>
<td>-3.13</td>
<td>-0.372</td>
<td>(0.039)</td>
<td>8.46</td>
<td>5.33</td>
</tr>
<tr>
<td># of felony arrests, age 40</td>
<td>40</td>
<td>-1.14</td>
<td>-0.266</td>
<td>(0.092)</td>
<td>3.26</td>
<td>2.12</td>
</tr>
<tr>
<td># of adult arrests (misd.+fel.), age 40</td>
<td>40</td>
<td>-4.26</td>
<td>-0.373</td>
<td>(0.041)</td>
<td>11.7</td>
<td>7.46</td>
</tr>
<tr>
<td># of lifetime arrests, age 40</td>
<td>40</td>
<td>-4.20</td>
<td>-0.346</td>
<td>(0.053)</td>
<td>12.4</td>
<td>8.21</td>
</tr>
<tr>
<td>Employed, age 40</td>
<td>40</td>
<td>0.200</td>
<td>0.394</td>
<td>(0.024)</td>
<td>0.500</td>
<td>0.700</td>
</tr>
<tr>
<td>Use heroin, age 40</td>
<td>40</td>
<td>-0.143</td>
<td>-0.402</td>
<td>(0.088)</td>
<td>0.143</td>
<td>0.000</td>
</tr>
<tr>
<td>Sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>72</td>
<td>39</td>
</tr>
</tbody>
</table>

Notes: Statistics are shown for the outcomes analyzed in this paper. There are differences in treatment effects by gender although strong effects are found for both. “CAT total” denotes the California Achievement Test total score normalized to control mean zero and variance of one. Test statistics are corrected for the effect of multiple hypothesis testing and threats to validity (see Heckman et al., 2010, Conti et al., 2012). The reported effect is the difference in means between treatment and control groups. The effect size is the ratio of the effect to the standard deviation of the control group. Stars denote statistical significance: ** - 1 percent level, * - 5 percent level, * - 10 percent level. Monthly income is adjusted to thousands of year-2006 dollars using annual national CPI.
Table 3: Some Selected Program Treatment Effects (Females)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Age</th>
<th>Treatment Effect</th>
<th>Control Group</th>
<th>Treatment Group</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Effect</td>
<td>Effect Size</td>
<td>p-value</td>
</tr>
<tr>
<td>CAT total, age 8</td>
<td>8</td>
<td>0.565 *</td>
<td>0.614</td>
<td>(0.062)</td>
</tr>
<tr>
<td>CAT total, age 14</td>
<td>14</td>
<td>0.806 **</td>
<td>0.909</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Any special education, age 14</td>
<td>14</td>
<td>-0.262 **</td>
<td>-0.514</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Mentally impaired at least once, age 19</td>
<td>19</td>
<td>-0.280 **</td>
<td>-0.569</td>
<td>(0.017)</td>
</tr>
<tr>
<td># of misdemeanor violent crimes, age 27</td>
<td>27</td>
<td>-0.423 **</td>
<td>-0.292</td>
<td>(0.032)</td>
</tr>
<tr>
<td># of felony arrests, age 27</td>
<td>27</td>
<td>-0.269 **</td>
<td>-0.325</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Jobless for more than 1 year, age 27</td>
<td>27</td>
<td>-0.292 *</td>
<td>-0.573</td>
<td>(0.071)</td>
</tr>
<tr>
<td>Ever tried drugs other than alcohol or weed, age 27</td>
<td>27</td>
<td>-0.227 **</td>
<td>-0.530</td>
<td>(0.045)</td>
</tr>
<tr>
<td># of misdemeanor violent crimes, age 40</td>
<td>40</td>
<td>-0.537 **</td>
<td>-0.364</td>
<td>(0.016)</td>
</tr>
<tr>
<td># of felony arrests, age 40</td>
<td>40</td>
<td>-0.383 **</td>
<td>-0.425</td>
<td>(0.028)</td>
</tr>
<tr>
<td># of lifetime violent crimes, age 40</td>
<td>40</td>
<td>-0.574 **</td>
<td>-0.384</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Months in all marriages, age 40</td>
<td>40</td>
<td>39.6 *</td>
<td>0.539</td>
<td>(0.076)</td>
</tr>
<tr>
<td>Ever on welfare, age 40</td>
<td>40</td>
<td>-0.163 **</td>
<td>-0.600</td>
<td>(0.031)</td>
</tr>
</tbody>
</table>

Sample 51 26 25

Notes: Statistics are shown for the outcomes analyzed in this paper. There are differences in treatment effects by gender although strong effects are found for both. “CAT total” denotes the California Achievement Test total score normalized to control mean zero and variance of one. Test statistics are corrected for the effect of multiple hypothesis testing and threats to validity (see Heckman et al., 2010, Conti et. al, 2012). The reported effect is the difference in means between treatment and control groups. The effect size is the ratio of the effect to the standard deviation of the control group. Stars denote statistical significance: *** - 1 percent level, ** - 5 percent level, * - 10 percent level. Monthly income is adjusted to thousands of year-2006 dollars using annual national CPI.
Table 4: Testing the Equality of Intercepts and Coefficients for Treatment and Control Groups in the Measurement Equation\(^{(a)}\)

<table>
<thead>
<tr>
<th>Factor</th>
<th>Age</th>
<th>Intercepts(^{(b)})</th>
<th>Coefficients(^{(c)})</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Males</td>
<td>Females</td>
</tr>
<tr>
<td>Cognition</td>
<td>7–9</td>
<td>test statistic</td>
<td>3.057</td>
</tr>
<tr>
<td></td>
<td></td>
<td>p-value</td>
<td>(.217)</td>
</tr>
<tr>
<td>Externalizing Behavior</td>
<td>7–9</td>
<td>test statistic</td>
<td>10.620</td>
</tr>
<tr>
<td></td>
<td></td>
<td>p-value</td>
<td>(.101)</td>
</tr>
<tr>
<td>Academic Motivation</td>
<td>7–9</td>
<td>test statistic</td>
<td>2.354</td>
</tr>
<tr>
<td></td>
<td></td>
<td>p-value</td>
<td>(.308)</td>
</tr>
</tbody>
</table>
Table 5: Rank Correlations among Externalizing Behavior, Academic Motivation and Noncognitive parts of Measures of Achievement, Males

<table>
<thead>
<tr>
<th>Vars</th>
<th>Age</th>
<th>Externalizing Behavior, age 7–9</th>
<th>Academic Motivation, age 7–9</th>
<th>California Achievement Test, age 14</th>
<th>Average High School GPA, age 15–18</th>
<th>APL age 19</th>
<th>APL age 27</th>
</tr>
</thead>
<tbody>
<tr>
<td>Externalizing Behavior</td>
<td>7–9</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Academic Motivation</td>
<td>7–9</td>
<td>0.449 ***</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.118)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>California Achievement Test</td>
<td>14</td>
<td>0.3154 **</td>
<td>0.692 ***</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.145)</td>
<td>(.110)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average High School GPA</td>
<td>15–18</td>
<td>0.1371</td>
<td>0.2886 **</td>
<td>0.4647 ***</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.155)</td>
<td>(.150)</td>
<td>(.150)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>APL</td>
<td>19</td>
<td>0.0405</td>
<td>0.2442 **</td>
<td>0.4428 ***</td>
<td>0.355 ***</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.134)</td>
<td>(.130)</td>
<td>(.138)</td>
<td>(.146)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>APL</td>
<td>27</td>
<td>0.0527</td>
<td>0.2335 **</td>
<td>0.2608 **</td>
<td>0.3293 **</td>
<td>0.4123 ***</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.137)</td>
<td>(.134)</td>
<td>(.153)</td>
<td>(.151)</td>
<td>(.125)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Correlations are based on rank correlations. The significance levels are indicated by: *p < 0.1, **p < 0.05, ***p < 0.01.
## Table 6: Rank Correlations among Externalizing Behavior, Academic Motivation and Noncognitive parts of Measures of Achievement, Females

<table>
<thead>
<tr>
<th>Vars</th>
<th>Age</th>
<th>Externalizing Behavior, age 7–9</th>
<th>Academic Motivation, age 7–9</th>
<th>California Achievement Test, age 14</th>
<th>Average High School GPA, age 15–18</th>
<th>APL age 19</th>
<th>APL age 27</th>
</tr>
</thead>
<tbody>
<tr>
<td>Externalizing Behavior</td>
<td>7–9</td>
<td>1</td>
<td></td>
<td>0.4258 ***</td>
<td>0.2177 ***</td>
<td>0.0065</td>
<td>0.191</td>
</tr>
<tr>
<td>Academic Motivation</td>
<td>7–9</td>
<td>0.4258 ***</td>
<td>0.5496 ***</td>
<td>0.0065</td>
<td>0.2711 *</td>
<td>0.0403</td>
<td>0.191</td>
</tr>
<tr>
<td>California Achievement Test</td>
<td>14</td>
<td>0.2177 ***</td>
<td>0.5496 ***</td>
<td>0.0403</td>
<td>0.2711 *</td>
<td>0.0403</td>
<td>0.191</td>
</tr>
<tr>
<td>Average High School GPA</td>
<td>15–18</td>
<td>0.0065</td>
<td>0.2711 *</td>
<td>0.0403</td>
<td>0.2711 *</td>
<td>0.0403</td>
<td>0.191</td>
</tr>
<tr>
<td>APL</td>
<td>19</td>
<td>0.0403</td>
<td>0.1479</td>
<td>0.3766 **</td>
<td>0.2662 *</td>
<td>0.0403</td>
<td>0.191</td>
</tr>
<tr>
<td>APL</td>
<td>27</td>
<td>0.191</td>
<td>0.5513 ***</td>
<td>0.6064 ***</td>
<td>0.4791 ***</td>
<td>0.5018 ***</td>
<td></td>
</tr>
</tbody>
</table>

Heckman The Economics/Econometrics
Appendix 3: Invariance of the Decompositions to Linear Transformations of Measurements
Our outcome decomposition (Equation (12)) is invariant to
linear transformations of measures.

Let $M^*_{m^j,d}$ be a linear transformation of the measure $M^j_{m^j,d}$, for
some $j \in J_p$ and $m^j \in M^j$. Specifically, we define $M^*_{m^j,d}$ by:

$$M^*_{m^j,d} = \kappa_1 (M^j_{m^j,d} + \kappa_2) \text{ such that } \kappa_1 \in \mathbb{R} \setminus \{0\}, \kappa_2 \in \mathbb{R}, \text{ and } d \in \{0, 1\}.$$

Let $\phi^*_{m^j}, \eta^*_{m^j}, \nu^*_{m^j}$ be the factor loading, error term and
intercept associated with the transformed measure $M^*_{m^j,d}, d \in \{0, 1\}$. 
Assume that $m^j \neq 1$,

1. From Equation (27) we obtain that $\varphi^*_m^j = \kappa_1 \varphi^j_m$.

2. From Equation (29) we can write:

$$\text{Var}(\eta^*_m) = \kappa_1^2 ([\varphi^j_m]^2 \cdot \text{Var}(\theta^j_d) - \text{Var}(M^j_{m,i,d})) = \kappa_1^2 \text{Var}(\eta^j_m).$$

3. Notice that the factor means remain the same if $M^*_m, d \in \{0, 1\}$ is not the first measure of skill $j$.

4. From Equation (31) we obtain that:

$$\nu^*_m = E(M^*_m, d) - \varphi^*_m \mu^j_d$$

$$= \kappa_1 (E(M^j_{m,i,d}) + \kappa_2) - \kappa_1 \varphi^j_m \mu^j_d$$

$$= \kappa_1 (E(M^j_{m,i,d}) - \varphi^j_m \mu^j_d) + \kappa_2 \kappa_1$$

$$= \kappa_1 (\nu^j_m + \kappa_2).$$

5. The factor loadings of the outcome equation are still identified by the covariance structure of the outcome and the first measure of each skill.
An affine transformation of a measure (that is not the first one) of some skill \( j \) does not affect the outcome factor loadings \( \alpha \) nor the factor means difference \( \mu^j_1 - \mu^j_0 \).

Now suppose the linear transformation is applied to the first measure.

Let \( M^*_{1,d} \) be a linear transformation of the measure \( M^j_{1,d} \), for some \( j \in \mathcal{J}_p \). Specifically, we define \( M^*_{1,d} \) by:
\[
M^*_{1,d} = \kappa_1 (M^j_{1,d} + \kappa_2) \quad \text{such that} \quad \kappa_1 \in \mathbb{R} \setminus \{0\}, \kappa_2 \in \mathbb{R}, \text{ and } d \in \{0, 1\}.
\]

Let \( \varphi^*_1, \eta^*_1, \nu^*_1 \) be the factor loading, error term and intercept associated with the transformed measure \( M^*_{1,d}, d \in \{0, 1\} \).

Let \( (\mu^*_{d}, d \in \{0, 1\}), (\alpha^*_{j'}, j' \in \mathcal{J}_p) \) and \( (\Sigma^*_{d}, d \in \{0, 1\}) \) be the new factor means, the outcome factor loadings and the factor covariance when the transformed measure \( M^*_{1,d}, d \in \{0, 1\} \) replaces the original measure \( M^j_{1,d}, d \in \{0, 1\} \).

We denote the element in the \( j \)-th line and \( j' \)-th column of a matrix \( A \) by \( A(j, j') \).
1. We set the factor location by normalizing $\nu^*_1$ to zero. Thus from Equation (26) we obtain:

$$\mu^*_d = E(M^*_1,d)$$

$$= \kappa_1(\mu^j_d + \kappa_2)$$

$$\therefore \mu^*_1 - \mu^*_0 = \kappa_1(\mu^j_1 - \mu^j_0).$$

Moreover, $\mu^*_1 - \mu^*_0 = (\mu^j_1 - \mu^j_0) \forall j' \in J_p \setminus \{j\}$. 

2. We set the factor scale by normalizing $\varphi^*_1$ to one. From Equation (30) we obtain:

$$\text{Cov}(M^*_1,d, M^j_1,d) = \kappa_1 \text{Cov}(M^j_1,d, M^j_1,d) \forall j' \in J_p, j' \neq j. \quad (33)$$
We use Equation (33) to compute elements of $\Sigma^*_d$ in terms of elements of $\Sigma_d$

\[
\Sigma^*_d(j, j) = \frac{\text{Cov}(M^*_1, M^j_1, d) \text{Cov}(M^*_1, M^j_{(m')}, d)}{\text{Cov}(M^j_{m'}, M^j_{(m')}, d)}
\]

\[
= \kappa_1^2 \frac{\text{Cov}(M^j_1, M^j_{m'}, d) \text{Cov}(M^j_1, M^j_{(m')}, d)}{\text{Cov}(M^j_{m'}, M^j_{(m')}, d)}
\]

\[
= \kappa_1^2 \Sigma_d(1, 1)
\]

Moreover, for all $j' \in \mathcal{J}_p; j' \neq j$, we can write:

\[
\Sigma^*_d(j, j') = \text{Cov}(M^*_1, M^j_1, d)
\]

\[
= \kappa_1 \text{Cov}(M^j_1, M^j_{j'}, d)
\]

\[
= \kappa_1 \Sigma_d(j, j')
\]

Thus we can write $\Sigma^*_d = I^* \Sigma_d I^*$, where $I^*$ is a $|\mathcal{J}_p|$-dimensional diagonal matrix such that $I^*(j, j) = \kappa_1$ and $I^*(j', j') = 1$ for all $j' \in \mathcal{J}_p; j' \neq j$. 
The covariance between outcome $Y_d, d \in \{0, 1\}$ and measure $M^*_{1,d}$ is given by:

$$\text{Cov}(Y_d, M^*_{1,d}) = \kappa_1 \text{Cov}(Y_d, M^j_{1,d}).$$

We can stack the covariance of outcome $Y_d$ across the first measures of skills $j \in \mathcal{J}_p$ to obtain

$$\text{Cov}(Y_d, M^*_{1,d}) = [\text{Cov}(Y_d, M^1_{1,d}); \ldots ; \text{Cov}(Y_d, M^j_{1,d}); \ldots ; \text{Cov}(Y_d, M^{|\mathcal{J}_p|}_{1,d})].$$

Thus $\text{Cov}(Y_d, M^*_{1,d}) = I^* \text{Cov}(Y_d, M_{1,d}).$

Notice that we can identify $\alpha$ through the equation

$$\text{Cov}(Y_d, M_{1,d}) = \Sigma \theta_d \alpha_d.$$ The equivalent equation for measure $M^*_{1,d}$ is given by:

$$\text{Cov}(Y_d, M^*_{1,d}) = \Sigma^* \theta_d \alpha^* \Rightarrow I^* \text{Cov}(Y_d, M_{1,d}) =$$

$$I^* \Sigma \theta_d I^* \alpha^* \Rightarrow \text{Cov}(Y_d, M_{1,d}) = \Sigma \theta_d I^* \alpha^*.$$

Therefore $\alpha^* = \alpha^j / \kappa_1$ and $\alpha^{*j'} = \alpha^{j'} \ \forall j' \in \mathcal{J}_p; j' \neq j.$
• From items (1)–(5) in the above list we can conclude that 
\[ \alpha^*j(\mu^*_1 - \mu^*_0) = \alpha^j(\mu^j_1 - \mu^j_0) \quad \forall j \in J_p. \]

• Thus a linear transformation of the first measure for any skill \( j \) does not change our outcome decomposition.
Appendix 4: Factor Regression
Measurement Error Correction for Using Estimated Factor Scores
Our approach is based on a three-step procedure.

We use a measurement system to evaluate factor scores $\theta_S$, which, in turn, are used as covariates in outcome equations.

Below is description of the three steps.

1. First, a common factor model is estimated for each latent variable. The vector of these latent variables for person $i$ is denoted by $\theta_i$.

2. Second, factor scores of $\theta$ are estimated for each participant $i$, based on the estimated parameters of the first step. We denote the vector of obtained factor scores by $\theta_{S,i}$.

3. Finally, ordinary linear regression is performed using the factor scores and target outcomes, producing estimators of the effects of factors in the outcome equations.
Formally, let the measurement system for agent $i$, $i \in \{1, \ldots, N\}$ be written as:

$$
\begin{align*}
\mathcal{M}_i &= \varphi \theta_i + \eta_i, \\
|\mathcal{M}| \times 1 &\quad |\mathcal{M}| \times |\mathcal{J}| &\quad |\mathcal{J}| \times 1 &\quad |\mathcal{M}| \times 1
\end{align*}
$$

where $\varphi$ represents a matrix of the factor loadings estimated in the first step and $\mathcal{M}_i$ is the vector of stacked measures for participant $i$ subtracted by the respective measurement intercepts $\nu_{m_i}$.

The dimension of each term is shown beneath it, with $\mathcal{M} = \bigcup_{j \in \mathcal{J}_p} \mathcal{M}^j$ being the union of all measure index sets.

Let $\text{Cov}(\eta_i, \eta_i) = \Omega$.

Assume that the $(\theta_i, \eta_i)$ are independent across the participants.

Let $\text{Cov}(\mathcal{M}_i, \mathcal{M}_i) = \Sigma$, $\text{Cov}(\theta_i, \theta_i) = \Phi$ and $\text{Cov}(\eta_i, \eta_i) = \Omega$. 
• Linear unbiased estimators are obtained if the matrix relationship $L'\varphi = I_{|J|}$ is satisfied.

• Bartlett’s estimator is based on the restricted minimization of mean square error subject to $L'\varphi = I_{|J|}$, which guarantees unbiasedness.

• Barlett’s estimator is given by

$$L^{B'} = (\varphi' \Omega^{-1} \varphi)^{-1} \varphi' \Omega^{-1}. \quad (34)$$

• The factor score predictor is written as

$$\theta^B_{S,i} = L^{B'} M_i = (\varphi' \Omega^{-1} \varphi)^{-1} \varphi' \Omega^{-1} M_i. \quad (35)$$
Correcting for Estimation Error in the Factor Scores

- Consider the model

\[ Y_i = \alpha \theta_i + \gamma Z_i + \epsilon_i, \quad i = 1, \ldots, N. \]  

(36)

- The Covariance matrix of \((\theta_i, Z_i)\) is

\[
\begin{pmatrix}
\Sigma_{\theta,\theta} & \Sigma_{\theta,Z} \\
\Sigma_{Z,\theta} & \Sigma_{Z,Z}
\end{pmatrix}.
\]

- It is assumed that \(\theta_i\) can be only measured with error. Let \(\theta_{S,i}\) be a measure of \(\theta_i\), thus we have:

\[
\theta_{S,i} = \theta_i + V_i, \quad i = 1, \ldots, N;
\]

\((Z_i, \theta_i) \perp \perp V_i, \quad E(V_i) = 0, \quad \text{Cov}(V, V) = \Sigma_{VV}.\)

- We adopt the notation that uses \(\Sigma_{B,C}\) for \(\text{Cov}(B, C)\). Thus we denote \(\text{Cov}(\theta_{S,i}, \theta_{S,i})\) by \(\Sigma_{\theta_{S},\theta_{S}}\).
• Assume that the \((\theta_i, Z_i, \epsilon_i)\) are iid

\[
Y_i = \alpha \theta_{S,i} + \gamma Z_i + \epsilon_i - \alpha V_i. \quad (37)
\]

\[
\text{plim} \left( \begin{array}{c}
\hat{\alpha} \\
\hat{\gamma}
\end{array} \right) = \left( \begin{array}{cc}
\text{Cov}(\theta_S, \theta_S) & \text{Cov}(\theta_S, Z) \\
\text{Cov}(Z, \theta_S) & \text{Cov}(Z, Z)
\end{array} \right)^{-1} \left( \begin{array}{cc}
\text{Cov}(\theta, \theta) & \text{Cov}(\theta, Z) \\
\text{Cov}(Z, \theta) & \text{Cov}(Z, Z)
\end{array} \right). \quad (38)
\]

\[
\text{plim} A^{-1} \left( \begin{array}{c}
\hat{\alpha} \\
\hat{\gamma}
\end{array} \right) = \left( \begin{array}{c}
\alpha \\
\gamma
\end{array} \right). \quad (39)
\]
Appendix 5: Correcting the Factor Regression Model for Measurement Errors
Consider the outcome model for agent $i$:

$$Y_i = \alpha \theta_i + \gamma Z_i + \epsilon_i,$$

(39)

- $(\theta_i, Z_i) \perp \perp \epsilon_i$ and $E(\epsilon_i) = 0$.
- $Z_i$ to denote pre-program variables, treatment status, and the intercept term of equation (10).
- From equation (55), the factor scores $\theta_{S,i}$ can be written as the skills $\theta_i$ plus a measurement error $V_i$, that is,

$$\theta_{S,i} = \theta_i + V_i$$

such that $(Z_i, \theta_i) \perp \perp V_i$ and $E(V_i) = 0$. (40)

- Replacing $\theta_i$ with $\theta_{S,i}$ yields $Y_i = \alpha \theta_{S,i} + \gamma Z_i + \epsilon_i - \alpha V_i$.
- The linear regression estimator of $\alpha$ and $\gamma$ is biased:

$$\text{plim} \left( \begin{array}{c} \hat{\alpha} \\ \hat{\gamma} \end{array} \right) = \left( \begin{array}{cc} \text{Cov}(\theta_{S}, \theta_{S}) & \text{Cov}(\theta_{S}, Z) \\ \text{Cov}(Z, \theta_{S}) & \text{Cov}(Z, Z) \end{array} \right)^{-1} \left( \begin{array}{cc} \text{Cov}(\theta, \theta) & \text{Cov}(\theta, Z) \\ \text{Cov}(Z, \theta) & \text{Cov}(Z, Z) \end{array} \right) \left( \begin{array}{c} \alpha \\ \gamma \end{array} \right).$$

(41)
• This is the multivariate version of the usual one-variable attenuation formula.

• All covariances in $A$ can be computed directly except for the terms that use $\theta$. The covariance $\text{Cov}(\theta, \theta)$ is estimated in step (1).

• Using equation (40), we can compute $\text{Cov}(Z, \theta_S) = \text{Cov}(Z, \theta)$. Thus, $A$ is identified.

• Our bias-correction procedure consists of pre-multiplying the least squares estimators $(\hat{\alpha}, \hat{\gamma})$ by $A^{-1}$, thus providing consistent estimates of $(\alpha, \gamma)$. 
Appendix 6: Separability Tests (Tests of Model Specification)
• First, we regress each of the unused measures on the treatment status indicator $D$, the estimated factors $\hat{\theta}$, and background variables $X$.

• Second, we create PBI and YRS indices (five in total) of the unused measures as defined by psychologists, and we run regressions analogous to those described for the unused measures using indices instead of each of the unused measures as dependent variables.

• We also check whether conditional on the extracted factors, the unused measures explain outcomes.

• We run two types of regressions.

• First, we regress outcomes on each of the unused measures, the estimated factors, $\hat{\theta}$, and background variables $X$. 
Table 7: Testing Whether the Treatment Effect on the Unused Measures is Zero

<table>
<thead>
<tr>
<th>Measures</th>
<th>Effect</th>
<th>Std. Error</th>
<th>p-value</th>
<th>Adjusted (a)</th>
<th>Effect</th>
<th>Std. Error</th>
<th>p-value</th>
<th>Adjusted (a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PBI requires continuous supervision</td>
<td>-0.221</td>
<td>0.159</td>
<td>0.914</td>
<td>-</td>
<td>0.628</td>
<td>0.249</td>
<td>0.009</td>
<td>0.401</td>
</tr>
<tr>
<td>PBI appears depressed</td>
<td>-0.010</td>
<td>0.235</td>
<td>0.518</td>
<td>-</td>
<td>0.22</td>
<td>0.222</td>
<td>0.031</td>
<td></td>
</tr>
<tr>
<td>YRS prediction of future academic success</td>
<td>0.028</td>
<td>0.127</td>
<td>0.412</td>
<td>-</td>
<td>0.432</td>
<td>0.191</td>
<td>0.054</td>
<td></td>
</tr>
<tr>
<td>YRS social relationship with class mates</td>
<td>0.086</td>
<td>0.223</td>
<td>0.350</td>
<td>-</td>
<td>0.319</td>
<td>0.173</td>
<td>0.068</td>
<td></td>
</tr>
<tr>
<td>YRS level of academic readiness</td>
<td>0.171</td>
<td>0.148</td>
<td>0.126</td>
<td>-</td>
<td>0.267</td>
<td>0.173</td>
<td>0.068</td>
<td></td>
</tr>
<tr>
<td>PBI learning retained well</td>
<td>-0.060</td>
<td>0.168</td>
<td>0.639</td>
<td>-</td>
<td>0.190</td>
<td>0.127</td>
<td>0.073</td>
<td></td>
</tr>
<tr>
<td>PBI blames others for troubles</td>
<td>0.064</td>
<td>0.195</td>
<td>0.373</td>
<td>-</td>
<td>0.381</td>
<td>0.286</td>
<td>0.096</td>
<td></td>
</tr>
<tr>
<td>PBI impulsive</td>
<td>-0.121</td>
<td>0.224</td>
<td>0.704</td>
<td>-</td>
<td>0.308</td>
<td>0.237</td>
<td>0.101</td>
<td></td>
</tr>
<tr>
<td>PBI appears generally happy</td>
<td>0.017</td>
<td>0.245</td>
<td>0.473</td>
<td>-</td>
<td>0.322</td>
<td>0.262</td>
<td>0.114</td>
<td></td>
</tr>
<tr>
<td>PBI uninterested in subject matter</td>
<td>-0.103</td>
<td>0.165</td>
<td>0.734</td>
<td>-</td>
<td>0.254</td>
<td>0.218</td>
<td>0.127</td>
<td></td>
</tr>
<tr>
<td>PBI isolated, few or no friends</td>
<td>0.384</td>
<td>0.267</td>
<td>0.078</td>
<td>-</td>
<td>0.413</td>
<td>0.363</td>
<td>0.132</td>
<td></td>
</tr>
<tr>
<td>PBI easily led into trouble</td>
<td>0.005</td>
<td>0.174</td>
<td>0.489</td>
<td>-</td>
<td>0.263</td>
<td>0.322</td>
<td>0.133</td>
<td></td>
</tr>
<tr>
<td>YRS social relationship with teacher</td>
<td>-0.065</td>
<td>0.279</td>
<td>0.591</td>
<td>-</td>
<td>0.240</td>
<td>0.234</td>
<td>0.157</td>
<td></td>
</tr>
<tr>
<td>PBI seeks constant reassurance</td>
<td>-0.398</td>
<td>0.234</td>
<td>0.953</td>
<td>-</td>
<td>0.306</td>
<td>0.363</td>
<td>0.203</td>
<td></td>
</tr>
<tr>
<td>PBI motivated toward academic performance</td>
<td>-0.314</td>
<td>0.120</td>
<td>0.994</td>
<td>-</td>
<td>0.084</td>
<td>0.130</td>
<td>0.362</td>
<td></td>
</tr>
<tr>
<td>YRS level of emotional adjustment</td>
<td>-0.164</td>
<td>0.202</td>
<td>0.790</td>
<td>-</td>
<td>0.162</td>
<td>0.252</td>
<td>0.263</td>
<td></td>
</tr>
<tr>
<td>PBI attempts to manipulate adults</td>
<td>-0.422</td>
<td>0.183</td>
<td>0.987</td>
<td>-</td>
<td>0.078</td>
<td>0.127</td>
<td>0.272</td>
<td></td>
</tr>
<tr>
<td>PBI shows positive leadership</td>
<td>0.082</td>
<td>0.225</td>
<td>0.359</td>
<td>-</td>
<td>0.144</td>
<td>0.242</td>
<td>0.278</td>
<td></td>
</tr>
<tr>
<td>YRS degree of trust of total environment</td>
<td>0.042</td>
<td>0.160</td>
<td>0.398</td>
<td>-</td>
<td>0.116</td>
<td>0.237</td>
<td>0.314</td>
<td></td>
</tr>
<tr>
<td>PBI completes assignments</td>
<td>-0.249</td>
<td>0.134</td>
<td>0.966</td>
<td>-</td>
<td>0.044</td>
<td>0.111</td>
<td>0.347</td>
<td></td>
</tr>
<tr>
<td>yrs degree of imagination and creativity shown</td>
<td>0.052</td>
<td>0.177</td>
<td>0.385</td>
<td>-</td>
<td>0.112</td>
<td>0.326</td>
<td>0.366</td>
<td></td>
</tr>
<tr>
<td>PBI resentful of criticism or discipline</td>
<td>-0.256</td>
<td>0.257</td>
<td>0.838</td>
<td>-</td>
<td>0.070</td>
<td>0.224</td>
<td>0.379</td>
<td></td>
</tr>
<tr>
<td>PBI possessive of teacher</td>
<td>-0.236</td>
<td>0.223</td>
<td>0.852</td>
<td>-</td>
<td>0.015</td>
<td>0.314</td>
<td>0.481</td>
<td></td>
</tr>
<tr>
<td>YRS level of curiosity shown</td>
<td>-0.034</td>
<td>0.227</td>
<td>0.558</td>
<td>-</td>
<td>0.012</td>
<td>0.187</td>
<td>0.526</td>
<td></td>
</tr>
<tr>
<td>PBI withdrawn and uncommunicative</td>
<td>0.195</td>
<td>0.229</td>
<td>0.200</td>
<td>-</td>
<td>0.044</td>
<td>0.341</td>
<td>0.550</td>
<td></td>
</tr>
<tr>
<td>PBI positive concern for own education</td>
<td>-0.122</td>
<td>0.124</td>
<td>0.836</td>
<td>-</td>
<td>0.034</td>
<td>0.197</td>
<td>0.567</td>
<td></td>
</tr>
<tr>
<td>PBI inappropriate personal appearance</td>
<td>0.074</td>
<td>0.212</td>
<td>0.364</td>
<td>-</td>
<td>0.060</td>
<td>0.327</td>
<td>0.572</td>
<td></td>
</tr>
<tr>
<td>PBI friendly and well-received by other pupils</td>
<td>0.238</td>
<td>0.211</td>
<td>0.132</td>
<td>-</td>
<td>0.048</td>
<td>0.183</td>
<td>0.604</td>
<td></td>
</tr>
<tr>
<td>PBI poor personal hygiene</td>
<td>0.000</td>
<td>0.219</td>
<td>0.501</td>
<td>-</td>
<td>0.083</td>
<td>0.297</td>
<td>0.609</td>
<td></td>
</tr>
<tr>
<td>PBI absences or truancies</td>
<td>-0.040</td>
<td>0.214</td>
<td>0.574</td>
<td>-</td>
<td>0.060</td>
<td>0.192</td>
<td>0.622</td>
<td></td>
</tr>
<tr>
<td>YRS level of verbal communication</td>
<td>0.319</td>
<td>0.238</td>
<td>0.093</td>
<td>-</td>
<td>0.097</td>
<td>0.236</td>
<td>0.658</td>
<td></td>
</tr>
<tr>
<td>PBI resistant to teacher</td>
<td>-0.211</td>
<td>0.185</td>
<td>0.871</td>
<td>-</td>
<td>0.140</td>
<td>0.145</td>
<td>0.829</td>
<td></td>
</tr>
<tr>
<td>PBI disobedient</td>
<td>-0.086</td>
<td>0.124</td>
<td>0.754</td>
<td>-</td>
<td>0.193</td>
<td>0.075</td>
<td>0.992</td>
<td></td>
</tr>
<tr>
<td>Joint Test (d)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.352</td>
<td></td>
<td>0.221</td>
<td></td>
</tr>
</tbody>
</table>
A Criteria

1. Interpretability (at least in its psychological and intuitive content)
2. High correlation of traits within blocks “convergent validity”
3. Relatively low correlations across blocks “discriminant validity”

B We have 43 measures and extract 3 factors
Appendix 7: Identifying The Factor Structure

How to:

- Summarize data?
- Pick the dimension of the factor structure?
- Identify the factors used in the 3-step procedure?
- Link the extracted factors to interpretable psychological constructs?
Measures of Cognitive and Noncognitive Skills

1 Measure of cognition
   - Stanford-Binet Intelligence Test (Terman and Merrill, 1960)

2 Measures of noncognitive skills
   - 43 noncognitive measures in the Perry data that describe children’s personality traits.
   - These measures belong to two separate psychological inventories of noncognitive skills:
     ① Pupil Behavior Inventory (PBI)
     ② Ypsilanti Rating Scale (YRS).
Table 8: PBI Items Description

<table>
<thead>
<tr>
<th>Personal Behavior</th>
<th>Academic Motivation</th>
<th>Socio-Emotional State</th>
<th>Teacher Dependence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absences or truancies</td>
<td>Shows initiatives</td>
<td>Appears depressed</td>
<td>Seeks constant reassurance</td>
</tr>
<tr>
<td>Inappropriate personal appearance</td>
<td>Alert and interested in school work</td>
<td>Withdrawn and uncommunicative</td>
<td></td>
</tr>
<tr>
<td>Lying or cheating</td>
<td>Learning retained well</td>
<td>Friendly and well-received by other pupils</td>
<td>Posessive of teacher</td>
</tr>
<tr>
<td>Steals</td>
<td>Completes assignments</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Swears or uses obscene words</td>
<td>Motivated toward academic performance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poor personal hygiene</td>
<td>Positive concern for own education</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Hesitant to try, or gives up easily</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Uninterested in subject matter</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Shows positive leadership</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Classroom Conduct</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Blames others for troubles</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resistant to teachers</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attempts to manipulate adults</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Influences others toward troublemaking</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Impulsive</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Requires continuous supervision</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggressive toward peers</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disobedient</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Easily led into trouble</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resentful of criticism or discipline</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disrupts classroom procedures</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Teases or provokes students</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(C): Criterion (A): Academic (N): No
### Table 9: YRS Items Description

<table>
<thead>
<tr>
<th>Academic Potential</th>
<th>Social Development</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degree of imagination and creativity shown</td>
<td>Social relationship with classmates</td>
</tr>
<tr>
<td>(O)</td>
<td>(A/E/C)</td>
</tr>
<tr>
<td>Level of academic readiness</td>
<td>Social relationship with teachers</td>
</tr>
<tr>
<td>(C/A/O/IQ)</td>
<td>(A/C)</td>
</tr>
<tr>
<td>Prediction of future academic success</td>
<td>Level of curiosity shown</td>
</tr>
<tr>
<td>(C/A/O/IQ)</td>
<td>(O)</td>
</tr>
<tr>
<td>Verbal Skill</td>
<td>Emotional Adjustment</td>
</tr>
<tr>
<td>Level of verbal communication</td>
<td>Level of emotional adjustment</td>
</tr>
<tr>
<td>(IQ)</td>
<td>(N)</td>
</tr>
<tr>
<td></td>
<td>Degree of trust of total environment</td>
</tr>
<tr>
<td></td>
<td>(A/N)</td>
</tr>
</tbody>
</table>
Ways to Summarize Measures in an Interpretable Fashion

1. Form indices over PBI and YRS?
   i. Hard to interpret in terms of recent research in psychology (Big 5).
   ii. Indices highly correlated because they overlap in content.
   iii. Does not account for measurement error which has been shown to be substantial for psychological measures (Cunha and Heckman, 2008b; Cunha et al., 2010).
Ways to Summarize Measures in an Interpretable Fashion

1. Ignore the groupings used by the Perry psychologists and select measures from all of their scales based on common sense and previous research in psychology, such as their interpretability in terms of the Big Five.
   - Called “operationalization” in psychology.
   - Inherently subjective.
   - However, it produces an interpretable system of measurements.
Exploratory factor analysis (EFA) (Gorsuch, 2003; Thompson, 2004; Jennrich, 2007). Used to create the Big Five

i. EFA implements the notions of *convergent* and *discriminant validity* that are held to be desirable features of any measurement system in personality psychology (Thurstone, 1947 and Almlund et al., 2011).

ii. Constructs factors based on blocks of measurements such that within blocks, the measures are strongly intercorrelated with each other (possess convergent validity) and across blocks are weakly correlated (possess discriminant validity).

iii. EFA does **not** impose orthogonality of the factors, although orthogonality might emerge from an EFA.

Exploratory Factor Analysis

- First, estimate the dimension of $\Sigma_\theta$ (i.e., number of factors).
**Table 10: Results of Procedures Estimating the Number of Factors For All 46 Items**

<table>
<thead>
<tr>
<th>Procedure</th>
<th>Males</th>
<th>Females</th>
<th>Pooled</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scree</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Horn</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Onatski</td>
<td>2</td>
<td>3</td>
<td>-</td>
</tr>
</tbody>
</table>
Exploratory Factor Analysis
(For a Given Number of Factors)

Finding Dedicated Measures

- *Direct Quartimin* oblique rotation
  (Jennrich and Sampson, 1966)
- Procedure identifies blocks of measures that within blocks are strongly correlated with one factor (i.e. satisfy *convergent validity*) but are weakly correlated with other factors across blocks (i.e. satisfy *discriminant validity*).
Digression on Direct Quartimin Procedure

• Abstract from previous notation to consider the EFA problem.
• Use general notation for factors

\[
\begin{align*}
\hat{M} & = \hat{\mu} + \hat{\Lambda} + \hat{\Theta} + \hat{U} \\
\text{Observed Responses} & \quad \text{Means} \quad \text{Factor Loadings} \quad \text{Factors} \quad \text{Uniqueness}
\end{align*}
\]

• Components of \( \hat{U} \) mutually uncorrelated
Notation for Rotation

- Normalize each component of $\Theta$ to have unit variance.

$$\sum_M = \Lambda \Phi_\Theta \Lambda' + \Psi_U$$

$$\Phi_\Theta = \text{Cov}(\Theta) \quad \Psi_U = \text{Cov}(U)$$

- $\Psi_U$: diagonal
Steps in EFA

- Estimate $\Omega = \Lambda \Phi \Theta \Lambda'$ ("extraction").
- Estimate $\Lambda$ and $\Phi \Theta$ ("rotation").
Thurstone’s “Perfect Simple Structure”:
Dedicated measures

- Facilitates interpretability of the factor system.
- 3 Factors \((L = 3)\), 7 Measures \((P = 7)\)

\[
\Lambda = \begin{bmatrix}
1 & 0 & 0 \\
1 & 0 & 0 \\
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
0 & 0 & 1 \\
\end{bmatrix}
\]

Each measure loaded on a single factor.
• Measure of complexity $Q(\Lambda)$
• Penalizes Departures from Perfect Simple Structure.
• Normalize the data in $M$ to have unit variance.
• Define $A$: $\Omega = AA'$
  $A$ assumed to have full column rank

$$\Lambda = AT^{-1}$$
$$\Phi = TT'$$
Orthogonal Factor Analysis: $\Phi_\Theta = I$

- $T$ is orthogonal matrix.
- $T^{-1} = T'$.
- Rows of $\Lambda$ are orthogonal transformations of $A$.
- $TT' = I$. 
Oblique Factor Analysis

- Min \( Q(\Lambda) \) s.t. \( \text{Diag}(TT') = I \).
- General Criterion used in the literature:

\[
Q(\Lambda) = (1 - k) \sum_{i=1}^{P} \sum_{j=1}^{P} \sum_{l \neq j, l=1}^{L} \lambda^2_{ij} \lambda^2_{il} + k \sum_{j=1}^{L} \sum_{i=1}^{P} \sum_{i \neq l, l=1}^{P} \lambda^2_{ij} \lambda^2_{lj}.
\]

\[
\text{Row Complexity} + k \text{Column Complexity}
\]

- Direct Quartimin: \( k = 0 \).
- If \( Q(\Lambda) = 0 \) and \( k = 0 \), Thurstone’s model a has perfect simple structure.
Alternative Approach Based on Loss Functions (Jennrich, 2004)

\[ Q(\Lambda) = \sum_i \sum_j h(|\lambda_{ij}|) \]

Component Loss Criterion (CLC)

Thm: Jennrich (2004)

*If there is an oblique rotation \( \tilde{\Lambda} \) of \( A \) that has a perfect simple structure, and if \( h \) is a concave and nondecreasing, then \( \tilde{\Lambda} \) minimizes \( Q(\Lambda) \) over all oblique rotations of \( A \). Moreover if \( h \) is strictly concave any minimizer must have a perfect simple structure.\*
Relationship of CLC to Direct Quartimin

- Direct quartimin does not have CLC structure.
- Yet if the corresponding criterion for direct quartimin has $Q(\Lambda) = 0$, we also obtain perfect simple structure.
Other Approaches

We obtain measures based on standard EFA procedures described in the psychological literature (for reviews, see Tabachnick and Fidell, 2001, Thompson, 2004, and Costello and Osborne, 2005). We implement a stepwise procedure to obtain a stable set of dedicated measures based on the following rules:

1. Apply quartimin rotation and obtain factor loadings.
2. Exclude measures that have two or more loadings in any columns greater than 0.4 (the cross-loading problem).
3. Exclude measures that do not have loadings at least .6 or higher for at least one gender (the weak loading problem).

The procedure stops when the set of measures converge, that is, we obtain a stable set of measures based on the iterative application of rules 1 to 3.
### Table 11: Factor Loadings of a Three-Factor Model After Oblique Rotation

<table>
<thead>
<tr>
<th></th>
<th>Males</th>
<th>Females</th>
<th>Pooled</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stanford Binet, age 7</td>
<td>.666 (.099)</td>
<td>.030 (.099)</td>
<td>.123 (.116)</td>
</tr>
<tr>
<td>Stanford Binet, age 8</td>
<td>.700 (.086)</td>
<td>-.104 (.084)</td>
<td>.222 (.106)</td>
</tr>
<tr>
<td>Stanford Binet, age 9</td>
<td>.925 (.063)</td>
<td>.070 (.047)</td>
<td>.008 (.049)</td>
</tr>
<tr>
<td>Externalizing Behavior</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disrupts classroom procedures</td>
<td>-.084 (.072)</td>
<td>.782 (.065)</td>
<td>.176 (.088)</td>
</tr>
<tr>
<td>Swears or uses obscene words</td>
<td>-.154 (.076)</td>
<td>.732 (.075)</td>
<td>.235 (.094)</td>
</tr>
<tr>
<td>Steals</td>
<td>-.010 (.134)</td>
<td>.371 (.134)</td>
<td>.119 (.150)</td>
</tr>
<tr>
<td>Lying or cheating</td>
<td>-.155 (.095)</td>
<td>.569 (.101)</td>
<td>.332 (.115)</td>
</tr>
<tr>
<td>Influences others toward troublemaking</td>
<td>-.037 (.058)</td>
<td>.927 (.043)</td>
<td>-.028 (.066)</td>
</tr>
<tr>
<td>Aggressive toward peers</td>
<td>.260 (.077)</td>
<td>.841 (.065)</td>
<td>-.145 (.071)</td>
</tr>
<tr>
<td>Teases or provokes students</td>
<td>.053 (.078)</td>
<td>.834 (.063)</td>
<td>-.059 (.086)</td>
</tr>
<tr>
<td>Academic Motivation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shows Initiative</td>
<td>.076 (.051)</td>
<td>-.065 (.042)</td>
<td>.910 (.047)</td>
</tr>
<tr>
<td>Alert and interested in school work</td>
<td>.082 (.051)</td>
<td>.069 (.055)</td>
<td>.895 (.054)</td>
</tr>
<tr>
<td>Hesitant to try, or gives up easily</td>
<td>.049 (.088)</td>
<td>.195 (.100)</td>
<td>.664 (.093)</td>
</tr>
<tr>
<td>Sample size</td>
<td>59</td>
<td>37</td>
<td>96</td>
</tr>
</tbody>
</table>

Notes: Factor loadings based on the exploratory factor analysis with direct quartimin rotation are shown. Maximum likelihood asymptotic standard errors are in parentheses. Factor loadings relating factors to corresponding potential dedicated measures are in bold.
Follow Gorsuch (2003) and Thompson (2004), and derive a fully dedicated system as described by equations (14)–(16).

This procedure is an application of confirmatory factor analysis (CFA).

In our application, it produces an interpretable system that could have been picked using an “operationalization” approach.
### Table 12: Cognitive and Noncognitive Factors and Their Measures

<table>
<thead>
<tr>
<th>Cognition</th>
<th>Measures (a)</th>
<th>Age</th>
<th>Externalizing Behavior</th>
<th>Measures (a)</th>
<th>Age (b)</th>
<th>Academic Motivation</th>
<th>Measures (a)</th>
<th>Age (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stanford-Binet IQ</td>
<td>7</td>
<td>Disrupts classroom procedures</td>
<td>7–9</td>
<td>Shows initiative</td>
<td>7–9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stanford-Binet IQ</td>
<td>8</td>
<td>Swears or uses obscene words</td>
<td>7–9</td>
<td>Alert and interested in school work</td>
<td>7–9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stanford-Binet IQ</td>
<td>9</td>
<td>Steals</td>
<td>7–9</td>
<td>Hesitant to try, or gives up easily</td>
<td>7–9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Lying or cheating</td>
<td>7–9</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Influences others toward troublemaking</td>
<td>7–9</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Aggressive toward peers</td>
<td>7–9</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Teases or provokes students</td>
<td>7–9</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cronbach's alpha (c), males</td>
<td>0.838</td>
<td>Cronbach's alpha, males</td>
<td>0.906</td>
<td>Cronbach's alpha, males</td>
<td>0.901</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cronbach's alpha, females</td>
<td>0.913</td>
<td>Cronbach's alpha, females</td>
<td>0.916</td>
<td>Cronbach's alpha, females</td>
<td>0.896</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- These are related to standard preference parameters in economics (see Almlund et al., 2011).
In the Perry data, higher levels of externalizing behavior are strongly associated with adult crime.
E: Traits are Correlated over the Life Cycle

Figure 4: Spearman’s Rank Correlations between Externalizing Behavior at Ages 7–9 and # of Arrests by Ages 19, 27, and 40

*** - 1%, ** - 5%, * - 10% significance levels
Figure 5: Decompositions of Treatment Effects by Indices versus Factor Scores

Mentally impaired at least once, age 19 (-)
# of misdemeanor violent crimes, age 27 (-)
# of felony arrests, age 27 (-)
# of misdemeanor violent crimes, age 40 (-)
# of felony arrests, age 40 (-)
Use tobacco, age 27 (-)
Monthly income, age 27 (+)
# of felony arrests, age 27 (-)
Employed, age 40 (+)
# of lifetime arrests, age 40 (-)

Cognition  Externalizing Behavior  Academic Motivation  Other Factors
Appendix 8: Nonlinear Factor Analysis
• Start with linear system.
• Then generalized to nonlinear system.
• Our results already generalize the available results in linear systems.
• $Z_{a,k,t,j}$: $j^{th}$ measurement at time $t$ on measure of type $a$ for factor $k$

• Measurements for Child Capabilities:

$$Z_{1,k,t,j} = \mu_{1,k,t,j} + \alpha_{1,k,t,j} \theta_{k,t} + \varepsilon_{1,k,t,j}$$  \hspace{1cm} (42)

• Measurements for Investments:

$$Z_{2,k,t,j} = \mu_{2,k,t,j} + \alpha_{2,k,t,j} \theta_{k,t} + \varepsilon_{2,k,t,j}$$  \hspace{1cm} (43)

$$E(\varepsilon_{a,k,t,j}) = 0, j \in \{1, \ldots, M_{a,k,t}\}, t \in \{1, \ldots, T\},$$
$$k \in \{C, N\}, a \in \{1, 2\}$$
• Measurements on Parental Capabilities:

\[
Z_{3,k,1,j} = \mu_{3,k,1,j} + \alpha_{3,k,1,j} \theta_{k,P} + \varepsilon_{3,k,1,j},
\]

\[
E(\varepsilon_{3,k,1,j}) = 0, j \in \{1, \ldots, M_{3,k,1}\}, \text{ and } k \in \{C, N\}.
\]
• Set the scale of the factors by assuming \( \alpha_{a,k,t,1} = 1 \)
• Normalize \( E(\theta_{k,t}) = 0 \) and \( E(I_{k,t}) = 0 \) for all \( k \in \{C, N\}, t = 1, \ldots, T \)
• Trivial to identify the mean functions \( \mu_{a,k,t,j} \), \( a \in \{1, 2, 3\}, t \in \{1, \ldots, T\}, k \in \{C, N\} \)
Identification of the Factor Loadings and of the Joint Distributions of the Latent Variables

- Establish identification of the factor loadings assuming:
  a. That the $\varepsilon_{a,k,t,j}$ are uncorrelated across $t$
  b. That the analyst has at least two measures of child skills and investments in each period $t$, where $T \geq 2$. 
• Compute $\text{Cov} (Z_{1,c,t,1}, Z_{1,c,t+1,1})$
• Normalize $\alpha_{1,c,t,1} = 1$ for all $t$
• \[ \text{Cov} (Z_{1,c,t,1}, Z_{1,c,t+1,1}) = \text{Cov} (\theta_{c,t}, \theta_{c,t+1}). \] \hspace{1cm} (45)

• Covariance of the second measurement on cognitive skills at period \( t \) with the first measurement on cognitive skills at period \( t + 1 \):

\[ \text{Cov} (Z_{1,c,t,2}, Z_{1,c,t+1,1}) = \alpha_{1,c,t,2} \text{Cov} (\theta_{c,t}, \theta_{c,t+1}). \] \hspace{1cm} (46)

• If \( \text{Cov} (\theta_{c,t}, \theta_{c,t+1}) \neq 0 \)

\[ \frac{\text{Cov} (Z_{1,c,t,2}, Z_{1,c,t+1,1})}{\text{Cov} (Z_{1,c,t,1}, Z_{1,c,t+1,1})} = \alpha_{1,c,t,2}. \]
• If there are more than two measures of cognitive skill in each period $t$, one can identify $\alpha_{1,C,t,j}$ for $j \in \{2, 3, \ldots, M_{1,C,t}\}$, $t \in \{1, \ldots, T\}$ up to the normalization $\alpha_{1,C,t,1} = 1$.

• The assumption that the $\varepsilon_{a,k,t,j}$ are uncorrelated across $t$ is then no longer necessary.
• Replacing $Z_{1,C,t+1,1}$ by $Z_{a',k',t',3}$ for some $(a', k', t')$ which may or may not be equal to $(1, C, t)$, we may proceed in the same fashion.

• Thus:

$$\frac{\text{Cov} (Z_{1,C,t,2}, Z_{a',k',t',3})}{\text{Cov} (Z_{1,C,t,1}, Z_{a',k',t',3})} = \frac{\alpha_{1,C,t,2} \alpha_{a',k',t',3}}{\alpha_{1,C,t,1} \alpha_{a',k',t',3}} \frac{\text{Cov} (\theta_{C,t}, \theta_{k',t'})}{\text{Cov} (\theta_{C,t}, \theta_{k',t'})}$$

$$= \frac{\alpha_{1,C,t,2}}{\alpha_{1,C,t,1}} = \alpha_{1,C,t,2}$$

• Only requires uncorrelatedness across different $j$ (measurements) but not across $t$. 
• Note that the same third measurement $Z_{a',k',t',3}$ can be reused for all $a$, $t$ and $k$ implying that in the presence of serial correlation, the total number of measurements required is $2L + 1$ if there are $L$ factors.

• To recover the distribution of $\theta$ note that

$$\frac{\text{known}}{\alpha_1, C, t, j} Z_{1, C, t, j} = \frac{\text{known}}{\alpha_1, C, t, j} \mu_{1, C, t, j} + \theta_{C, t} + \frac{\varepsilon_{1, C, t, j}}{\alpha_1, C, t, j}, j \in \{1, 2, \ldots, M_{1, C, t}\}.$$  \hspace{1cm} (47)
From Schennach (2004a,b), we can identify the joint distribution of all the latent variables \( p(\theta) \) for short.

\[
\theta = \left( \{ \theta_{C,t} \}_{t=1}^T , \{ \theta_{N,t} \}_{t=1}^T , \{ I_{C,t} \}_{t=1}^T , \{ I_{N,t} \}_{t=1}^T , \theta_{C,P} , \theta_{N,P} \right).
\]
Identification of the model can be secured (after the factor loadings are determined) if only two measurements of each latent factor are available.

\[ W_i = \left( \begin{array}{c} \frac{Z_1,C,t,i}{\alpha_1,C,t,i} \\ \frac{Z_1,N,t,i}{\alpha_1,N,t,i} \end{array} \right)_{t=1}^T, \left( \begin{array}{c} \frac{Z_2,C,t,i}{\alpha_2,C,t,i} \end{array} \right)_{t=1}^T, \left( \begin{array}{c} \frac{Z_2,N,t,i}{\alpha_2,N,t,i} \\ \frac{Z_3,C,1,i}{\alpha_3,C,1,i}, \frac{Z_3,N,1,i}{\alpha_3,N,1,i} \end{array} \right)'_{t=1}^T, \quad i \in \{1, 2\}. \]

\[ \omega_i = \left( \begin{array}{c} \frac{\varepsilon_1,C,t,i}{\alpha_1,C,t,i} \\ \frac{\varepsilon_1,N,t,i}{\alpha_1,N,t,i} \end{array} \right)_{t=1}^T, \left( \begin{array}{c} \frac{\varepsilon_2,C,t,i}{\alpha_2,C,t,i} \end{array} \right)_{t=1}^T, \left( \begin{array}{c} \frac{\varepsilon_2,N,t,i}{\alpha_2,N,t,i} \\ \frac{\varepsilon_3,C,1,i}{\alpha_3,C,1,i}, \frac{\varepsilon_3,N,1,i}{\alpha_3,N,1,i} \end{array} \right)'_{t=1}^T, \quad i \in \{1, 2\}. \]
Theorem 1

Let $W_1, W_2, \theta, \omega_1, \omega_2$ be random vectors taking values in $\mathbb{R}^L$ and related through

$$
W_1 = \theta + \omega_1 \\
W_2 = \theta + \omega_2.
$$

If (i) $E[\omega_1|\theta, \omega_2] = 0$ and (ii) $\omega_2$ is independent from $\theta$, then the density of $\theta$ can be expressed in terms of observable quantities as:

$$
p_{\theta}(\theta) = (2\pi)^{-L} \int e^{-i\chi \cdot \theta} \exp \left( \int_0^\chi \frac{E[iW_1 e^{i\zeta \cdot W_2}]}{E[e^{i\zeta \cdot W_2}]} \cdot d\zeta \right) d\chi,
$$

where $i = \sqrt{-1}$. This assumes that all the requisite expectations exist and $E[e^{i\zeta \cdot W_2}]$ is nonvanishing.
• The improvement in this analysis over the analysis of Cunha and Heckman (2008a) is that identification can be achieved under much weaker conditions regarding measurement errors—far fewer independence assumptions are needed.

• The asymmetry in the analysis of \( \omega_1 \) and \( \omega_2 \) generalizes previous analysis which treats these terms symmetrically.

• Our analysis accommodates heteroscedasticity in the distribution of \( \omega_1 \) that may depend on \( \omega_2 \) and \( \theta \).
The Identification of a General Measurement Error Model

- Can generalize linear factor models to a measurement model of the general form

\[ Z_j = a_j(\theta, \varepsilon_j) \text{ for } j \in \{1, \ldots, M\}, \]  

(48)

where \( M \geq 3 \) and where the indicator \( Z_j \) is observed while the latent factor \( \theta \) and the disturbance \( \varepsilon_j \) are not.
• Variables $Z_j$, $\theta$, and $\varepsilon_j$

$$Z_j = \left( \{Z_1, C, t, j\}_{t=1}^T, \{Z_1, N, t, j\}_{t=1}^T, \{Z_2, C, t, j\}_{t=1}^T, \{Z_2, N, t, j\}_{t=1}^T, \{Z_3, C, 1, j\}, \{Z_3, N, 1, j\} \right)'$$

$$\varepsilon_j = \left( \{\varepsilon_1, C, t, j\}_{t=1}^T, \{\varepsilon_1, N, t, j\}_{t=1}^T, \{\varepsilon_2, C, t, j\}_{t=1}^T, \{\varepsilon_2, N, t, j\}_{t=1}^T, \{\varepsilon_3, C, 1, j\}, \{\varepsilon_3, C, N, 1, j\} \right)'$$

As before, the vector of unobserved latent factors is:

$$\theta = \left( \{\theta_C, t\}_{t=1}^T, \{\theta_N, t\}_{t=1}^T, \{I_C, t\}_{t=1}^T, \{I_N, t\}_{t=1}^T, \theta_C, P, \theta_N, P \right)'$$

• The functions $a_j(\cdot, \cdot)$ for $j \in \{1, \ldots, M\}$ in equations (54) are unknown.
The distribution of $\theta$ in Equations (54) is identified under the following conditions:

1. The joint density of $\theta, Z_1, Z_2, Z_3$ is bounded and as are all of their marginal and conditional densities.

2. $Z_1, Z_2, Z_3$ are mutually independent conditional on $\theta$.

3. $p_{Z_1|Z_2}(Z_1 | Z_2)$ and $p_{\theta|Z_1}(\theta | Z_1)$ form a bounded, complete family of distributions indexed by $Z_2$ and $Z_1$, respectively.

4. Whenever $\theta \neq \tilde{\theta}$, $p_{Z_3|\theta}(Z_3 | \theta)$ and $p_{Z_3|\theta}(Z_3 | \tilde{\theta})$ differ over a set of strictly positive probability.

5. There exists a known functional $\Psi$, mapping a density to a vector, that has the property that $\Psi \left[ p_{Z_1|\theta}(\cdot | \theta) \right] = \theta$. 
• The conditional independence requirement of Assumption 2 is weaker than the full independence assumption traditionally made in standard linear factor models because it allows for heteroskedasticity.

• Versions of Assumption 3 appear in the nonparametric instrumental variable literature (e.g. Newey and Powell, 2003).

• The minimum number of measurements needed for identification is $2L + 1$, as in the linear case.
• Assumption 4 is automatically satisfied, for instance, if \( \theta \) is univariate and \( a_3(\theta, \varepsilon_3) \) is strictly increasing in \( \theta \).

• However, it holds much more generally.

• Since \( a_3(\theta, \varepsilon_3) \) is nonseparable, the distribution of \( Z_3 \) conditional on \( \theta \) can change with \( \theta \), thus making it possible for Assumption 4 to be satisfied even if \( a_3(\theta, \varepsilon_3) \) is not strictly increasing in \( \theta \).
• Assumption 5 specifies how the observed $Z_1$ is used to “anchor” the scale of the unobserved $\theta$.

• The most common choice of functional $\Psi$ would be the mean, the mode, the median, or any other well-defined measure of location.

• This specification allows for nonclassical measurement error.
• Theorem 2 *does not* claim that the distributions of the errors $\varepsilon_j$ or that the functions $a_j(\cdot, \cdot)$ are identified.

• In fact, it is always possible to alter the distribution of $\varepsilon_j$ and the dependence of the function $a_j(\cdot, \cdot)$ on its second argument in ways that cancel each other out, as noted in the literature on nonseparable models.
• However, lack of identifiability of these features of the model does not prevent identification of the distribution of $\theta$.

• Nevertheless, various normalizations ensuring that the functions $a_j(\theta, \varepsilon_j)$ are fully identified are available.

• For example, if each element of $\varepsilon_j$ is normalized to be uniform (or any other known distribution), the $a_j(\theta, \varepsilon_j)$ are fully identified.

• Other normalizations discussed in Matzkin (2003, 2007) are also possible.
• The assumptions used to generate Theorems 1 and 2 are not nested within each other.
• Their different assumptions represent different trade-offs best suited for different applications.
Nonparametric Identification of the Technology of Capability Formation

- Under assumptions which we now present, we can nonparametrically identify technology

\[ \theta_{j,t+1} = f_{j,s} (\theta_C, t, \theta_N, t, I_j, t, \theta_C, P, \theta_N, P, \eta_j, t) \]
- Normalize $\eta_{k,t}$ to have a uniform density on $[0, 1]$.
- Any of the normalizations suggested by Matzkin (2003, 2007) could be used.
- Assuming $\eta_{k,t}$ is uniform $[0, 1], f_{s,k}$ is nonparametrically identified.
Proof:

- We have just established how to identify:

$$\Pr \left[ \theta_{k,t+1} \leq \bar{\theta} | \theta_t, l_k,t, \theta_P \right] \equiv G \left( \bar{\theta} | \theta_t, l_k,t, \theta_P \right).$$

- $$f_{s,k} (\theta_t, l_k,t, \theta_P) = G^{-1} (\eta_{k,t} | \theta_t, l_k,t, \theta_P)$$

  $$G^{-1} (\eta_{k,t} | \theta_t, l_k,t, \theta_P)$$ denotes the inverse of $$G \left( \bar{\theta} | \theta_t, l_k,t, \theta_P \right)$$ with respect to its first argument

- i.e. the value $$\bar{\theta}$$ such that $$\eta_{k,t} = G \left( \bar{\theta} | \theta_t, l_k,t, \theta_P \right).$$
• The more traditional separable technology with zero mean disturbance, $\theta_{k,t+1} = f_{s,k}(\theta_t, l_{k,t}, \theta_P) + \eta_{k,t}$, is covered by our analysis if we define
\[
f_{s,k}(\theta_t, l_{k,t}, \theta_P) \equiv E[\theta_{k,t+1} \mid \theta_t, l_{k,t}, \theta_P]
\]
The density of $\eta_{k,t}$ conditional on all variables is identified from

$$p_{\theta_{k,t+1}|\theta_t,I_k,t,\theta_P}(\eta_{k,t} | \theta_t, I_k,t, \theta_P) =
\frac{p_{\theta_{k,t+1}|\theta_t,I_k,t,\theta_P}(\eta_{k,t} + E[\theta_{k,t+1} | \theta_t, I_k,t, \theta_P] | \theta_t, I_k,t, \theta_P),}{p_{\theta|\theta_t} \text{ is known once } p_{\theta} \text{ is known.}$$
Anchoring Skills in an Interpretable Metric

- It is common in the empirical literature on child schooling and investment and on value added models for test scores to measure capabilities – “ability” – by test scores.
- However, test scores are arbitrarily scaled.
- Any monotonic function of a test score is a test score.
- To gain a better understanding of the relative importance of cognitive and noncognitive skills and their interactions and the relative importance of investments at different stages of the life cycle, it is important to anchor skills in a common scale.
• Consider the effect of end of period \( T \) cognitive and noncognitive skills on adult outcomes \( Z_{4,j} \), for \( j \in \{1, \ldots, J\} \).

• \( J_1 \) observed outcomes that are linear functions of cognitive and noncognitive skills at the end of period \( T \):

\[
Z_{4,j} = \mu_{4,j} + \alpha_{4,C,j} \theta_{C,T} + \alpha_{4,N,j} \theta_{N,T} + \varepsilon_{4,j}, \quad j \in \{1, \ldots, J_1\}.
\]

• When adult outcomes are linear and separable functions of skills, define the anchoring functions to be:

\[
\begin{align*}
 g_{C,j}(\theta_{C,T}) &= \mu_{4,j} + \alpha_{4,C,j} \theta_{C,T}. \\
 g_{N,j}(\theta_{N,T}) &= \mu_{4,j} + \alpha_{4,N,j} \theta_{N,T}.
\end{align*}
\]
• We can also anchor using nonlinear functions. One example would be an outcome produced by a latent variable $Z_{4,j}^*$, for $j \in \{1, \ldots, J\}$:

$$Z_{4,j}^* = \tilde{g}_j(\theta_C, T, \theta_N, T) - \varepsilon_{4,j}.$$  

•

$$Z_{4,j} = \begin{cases} 
1, & \text{if } \tilde{g}_j(\theta_C, T, \theta_N, T) - \varepsilon_{4,j} \geq 0 \\
0, & \text{otherwise.}
\end{cases}$$
In this notation

\[
\Pr (Z_{4,j} = 1 | \theta_{C,T}, \theta_{N,T}) = \\
= \Pr [\varepsilon_{4,j} \leq \tilde{g}_j (\theta_{C,T}, \theta_{N,T}) | \theta_{C,T}, \theta_{N,T}] \\
= F_{\varepsilon_{4,j}} [\tilde{g}_j (\theta_{C,T}, \theta_{N,T}) | \theta_{C,T}, \theta_{N,T}] \\
= g_j (\theta_{C,T}, \theta_{N,T}).
\]
• We can identify Pr \[ Z_{4,j} = 1 \mid \theta_{C,T}, \theta_{N,T} \].

• We can extract two separate “anchors” \( g_{C,j}(\theta_{C,T}) \) and \( g_{N,j}(\theta_{N,T}) \) from the function \( g_j(\theta_{C,T}, \theta_{N,T}) \).

• Integrate out the other variable, e.g.,

\[
\begin{align*}
g_{C,j}(\theta_{C,T}) & \equiv \int g_j(\theta_{C,T}, \theta_{N,T}) p_{\theta_{N,T}}(\theta_{N,T}) \, d\theta_{N,T}, \\
g_{N,j}(\theta_{N,T}) & \equiv \int g_j(\theta_{C,T}, \theta_{N,T}) p_{\theta_{C,T}}(\theta_{C,T}) \, d\theta_{C,T},
\end{align*}
\]

where the marginal densities, \( p_{\theta_{j,T}}(\theta_{N,T}), j \in \{C, N\} \) are identified by applying the preceding analysis.
The “anchored” skills, denoted by $\tilde{\theta}_{j,k,t}$, are defined as
\[
\tilde{\theta}_{j,k,t} = g_{k,j}(\theta_{k,t}),
\]
\[k \in \{C, N\}, \quad t \in \{1, \ldots, T\}.
\]

The technology function expressed in terms of the anchored skills—denoted by $\tilde{f}_{j,s,k} \left(\tilde{\theta}_{j,t}, I_{k,t}, \theta_P, \eta_{k,t}\right)$—is also identified.

Redefine the technology function to be,
\[
\tilde{f}_{j,s,k} \left(\tilde{\theta}_{j,C,t}, \tilde{\theta}_{j,N,t}, I_{k,t}, \theta_{C,P}, \theta_{N,P}, \eta_{k,t}\right)
\equiv g_{k,j} \left(f_{s,k} \left(g_{C,j}^{-1} \left(\tilde{\theta}_{j,C,t}\right), g_{N,j}^{-1} \left(\tilde{\theta}_{j,N,t}\right), I_{k,t}, \theta_{C,P}, \theta_{N,P}, \eta_{k,t}\right)\right),
\]
\[k \in \{C, N\}
\]

$g_{k,j}^{-1} (\cdot)$ is the inverse of the function $g_{k,j} (\cdot)$. 
• Straightforward to show

\[
\tilde{f}_{j,s,k} \left( \tilde{\theta}_{j,C,t}, \tilde{\theta}_{j,N,t}, I_{k,t}, \theta_{C,P}, \theta_{N,P}, \eta_{k,t} \right) \\
= \tilde{f}_{j,s,k} \left( g_{C,j} (\theta_{C,t}), g_{N,j} (\theta_{N,t}), I_{k,t}, \theta_{C,P}, \theta_{N,P}, \eta_{k,t} \right) \\
= g_{k,j} \left( f_{s,k} \left( g_{C,j}^{-1} (g_{C,j} (\theta_{C,t})), g_{N,j}^{-1} (g_{N,j} (\theta_{N,t})), \right. \right. \\
\left. I_{k,t}, \theta_{C,P}, \theta_{N,P}, \eta_{k,t} \right) \\
= g_{k,j} \left( f_{s,k} (\theta_{C,t}, \theta_{N,t}, I_{k,t}, \theta_{C,P}, \theta_{N,P}, \eta_{k,t}) \right) \\
= g_{k,j} (\theta_{k,t+1}) = \tilde{\theta}_{j,k,t+1},
\]

as desired.

• Thus, \( \tilde{f}_{j,s,k} \) is the equation of motion for the anchored skills \( \tilde{\theta}_{j,k,t+1} \) that is consistent with the equation of motion \( f_{s,k} \) for the original skills \( \theta_{k,t} \).
Adding Endogenous Parental Investment

- Many economic models predict that parental investments in period $t$, $I_t$, should depend on parental skills, $(\theta_C, P, \theta_N, P)$, child’s skills at the beginning of period $t$, $(\theta_C, t, \theta_N, t)$, parental income, $y_t$, child’s unobservable heterogeneity, $\pi$, and parental wealth at period $t$, $y_t$.

- Write

$$I_{k,t} = g_{k,t}(\theta_C, t, \theta_N, t, \pi, \theta_C, P, \theta_N, P, y_t) + \zeta_{k,t},$$

$k \in \{C, N\}, t \in \{1, \ldots, T\}$ (51)

- $\zeta_{k,t} \perp \theta_t'$ for all $k$ and $t$, where the $\zeta_{k,t}$ can be unobserved state variables (such as wealth or unobserved inputs in the technology for the formation of skills) or investment shocks.
• To see how identification is secured, substitute (51) into equation (42) to obtain:

\[ Z_{2,k,t,j} = \mu_{2,k,t,j} + \alpha_{2,k,t,j} g_{k,t} \left( \theta_{C,t}, \theta_{N,t}, \pi, \theta_{C,P}, \theta_{N,P}, y_t \right) + \alpha_{2,k,t,j} \zeta_{k,t} + \varepsilon_{2,k,t,j} \]

for \( j \in \{1, \ldots, M_{2,k,t} \} \), \( t \in \{1, \ldots, T\} \), and \( k \in \{C, N\} \).

• From measurements on child skills, parental skills, child adult outcomes, and family income, we can obtain the joint distribution of \( (\theta_{C,t}, \theta_{N,t}, \pi, \theta_{C,P}, \theta_{N,P}, y_t) \).

• Alternatively can identify using exogenous variations in \( y_t \).
Sketch of Identification:

- Consider the model (deleting parental capacities)

\[
\theta_{j,i,t+1} = f_j(\theta_{i,t}, I_{i,t}) + \gamma \eta_i + \nu_{j,i,t}
\]

- Our analysis identifies the distribution of \((\theta_{i,t+1}, \theta_{i,t}, I_t \ldots)\)

\[
\Delta \theta_{j,i,t+1} = f_j(\theta_{i,t}, I_{i,t}) - f_j(\theta_{i,t-1}, I_{i,t-1}) + \nu_{j,i,t} - \nu_{j,i,t-1}
\]

- For endogenous investment, if parents know that \(\nu_{j,i,t}\) and \(\eta_i\) when making investments, \(I_{i,t}\) is not pre-determined.

- Suppose we have martingale increments

\[
E[\nu_{j,i,t} - \nu_{j,i,t-1} \mid \theta_{i,t}, \theta_{i,t-1}, \ldots, I_{i,t-1}, I_{i,t-2}, \ldots, \left\{y_{i,t}, y_{i,t-1}\right\}] = 0
\]
• If $f_j$ is parametric ($f_j(\theta_{i,t}, l_{i,t}, \beta)$), use GMM argument.

• Assume there exists a function

$$\phi(\theta_{i,t-1}, \theta_{i,t-2}, \ldots, l_{i,t-1}, l_{i,t-2}, \ldots, y_{i,t}, y_{i,t-1}, \ldots)$$

FOC:

$$E[(\theta_{j,i,t+1} - \theta_{j,i,t} - (f_j(\theta_{i,t}, l_{i,t}, \beta)) - f(\theta_{i,t-1}, l_{i,t-1}, \beta)) \cdot \phi'(\theta_{i,t-1}, \theta_{i,t-2}, \ldots, l_{i,t-1}, l_{i,t-2}, \ldots, y_{i,t}, y_{i,t-1}, \ldots)] = 0$$

• We can work with a sequence of income (and other family) shocks to identify the technology.
Assume

\[
E\left[ \frac{\partial}{\partial \beta} \left[ f_j(\theta_{i,t}, l_{i,t}, \beta) - f_j(\theta_{i,t-1}, l_{i,t-1}, \beta) \right] \right] \\
\phi'(\theta_{i,t-1}, \theta_{i,t-2}, \ldots, l_{t-1}, l_{t-2})
\]

has full rank.

\therefore \text{Identify } \beta \text{ if } (\theta_{i,t}, \theta_{i,t-1}, \ldots, l_{i,t}, \ldots, l_{i,t-1}) \text{ known.}
• Problem: We do not observe \((\theta, I)\).
• Since we determined \(P(\theta, I)\).
• We can estimate the model subject to constraint (53).
• Alternatively, form factor scores for \((\theta, I)\) and then estimate with GMM.
• Use as initial condition for the likelihood equation.
Appendix 9: Identifying the Nonlinear Technology using Dynamic Factor Models
Theorem 1

Let $W_1, W_2, \theta, \omega_1, \omega_2$ be random vectors taking values in $\mathbb{R}^L$ and related through

$$W_1 = \theta + \omega_1$$
$$W_2 = \theta + \omega_2.$$

If (i) $E[\omega_1|\theta, \omega_2] = 0$ and (ii) $\omega_2$ is independent from $\theta$, then the density of $\theta$ can be expressed in terms of observable quantities as:

$$p_{\theta}(\theta) = (2\pi)^{-L} \int e^{-i\chi \cdot \theta} \exp \left( \int \chi \cdot \frac{E[iW_1 e^{i\zeta \cdot W_2}]}{E[e^{i\zeta \cdot W_2}]} \cdot d\zeta \right) d\chi,$$

where $i = \sqrt{-1}$. This assumes that all the requisite expectations exist and $E[e^{i\zeta \cdot W_2}]$ is nonvanishing.

- Under additional restrictions can nonparametrically identify distributions of $\omega_1$ and $\omega_2$. 
The analysis accommodates heteroscedasticity in the distribution of $\omega_1$ that may depend on $\omega_2$ and $\theta$. 
Can generalize linear factor models to a measurement model of the general form

\[ Y_j = \psi_j (\theta, \varepsilon_j) \quad \text{for} \quad j \in \{1, \ldots, J\}, \]  

(54)

where \( J \geq 3 \) and where the indicator \( Y_j \) is observed while the latent factor \( \theta \) and the disturbance \( \varepsilon_j \) are not.
The distribution of $\theta$ is identified under the following conditions:

1. The joint density of $\theta$, $Y_1$, $Y_2$, $Y_3$ is bounded and as are all of their marginal and conditional densities.

2. $Y_1$, $Y_2$, $Y_3$ are mutually independent conditional on $\theta$.

3. $p_{Y_1|Y_2}(Y_1 \mid Y_2)$ and $p_{\theta|Y_1}(\theta \mid Y_1)$ form a bounded, complete family of distributions indexed by $Y_2$ and $Y_1$, respectively.

4. Whenever $\theta \neq \tilde{\theta}$, $p_{Y_3|\theta}(Y_3 \mid \theta)$ and $p_{Y_3|\theta}(Y_3 \mid \tilde{\theta})$ differ over a set of strictly positive probability.

5. There exists a known functional $\Psi$, mapping a density to a vector, that has the property that $\Psi \left[ p_{Y_1|\theta}(\cdot \mid \theta) \right] = \theta$. 

• Theorem 2 *does not* claim that the distributions of the errors $\varepsilon_j$ or that the functions $a_j(\cdot, \cdot)$ are identified.

• It is always possible to alter the distribution of $\varepsilon_j$ and the dependence of the function $a_j(\cdot, \cdot)$ on its second argument in ways that cancel each other out, as noted in the literature on nonseparable models.
• However, lack of identifiability of these features of the model does not prevent identification of the distribution of $\theta$.

• Nevertheless, various normalizations ensuring that the functions $a_j(\theta, \varepsilon_j)$ are fully identified are available.

• For example, if each element of $\varepsilon_j$ is normalized to be uniform (or any other known distribution), the $a_j(\theta, \varepsilon_j)$ are fully identified.

• Other normalizations discussed in Matzkin (2003, 2007) are also possible.
Nonparametric Identification of the Technology of Capability Formation

- Under assumptions presented below, we can nonparametrically identify technology

\[ \theta_{j,t+1} = f_j(\theta_{C,t}, \theta_{N,t}, l_{j,t}, \theta_{C,P}, \theta_{N,P}, \eta_{j,t}) \]
• Normalize $\eta_{k,t}$ to have a uniform density on $[0, 1]$.
• Any of the normalizations suggested by Matzkin (2003, 2007) could be used.
• Assuming $\eta_{k,t}$ is uniform $[0, 1]$, $f_j$ is nonparametrically identified.
Proof:

• We have just established how to identify:

$$\Pr [\theta_{k,t+1} \leq \bar{\theta} | \theta_t, l_{k,t}, \theta_P] \equiv G (\bar{\theta} | \theta_t, l_{k,t}, \theta_P).$$

• 

$$f_{t,k} (\theta_t, l_{k,t}, \theta_P) = G^{-1} (\eta_{k,t} | \theta_t, l_{k,t}, \theta_P)$$

$G^{-1} (\eta_{k,t} | \theta_t, l_{k,t}, \theta_P)$ denotes the inverse of $G (\bar{\theta} | \theta_t, l_{k,t}, \theta_P)$ with respect to its first argument.

• i.e. the value $\bar{\theta}$ such that $\eta_{k,t} = G (\bar{\theta} | \theta_t, l_{k,t}, \theta_P)$. 
The more traditional separable technology with zero mean disturbance, \( \theta_{k,t+1} = f_{t,k}(\theta_t, l_{k,t}, \theta_P) + \eta_{k,t} \), is covered by our analysis if we define

\[
f_{t,k}(\theta_t, l_{k,t}, \theta_P) \equiv E[\theta_{k,t+1} | \theta_t, l_{k,t}, \theta_P]
\]
• The density of $\eta_{k,t}$ conditional on all variables is identified from

$$p_{\theta_{k,t+1}\mid \theta_t, l_{k,t}, \theta_P} (\eta_{k,t} \mid \theta_t, l_{k,t}, \theta_P) =$$

$$p_{\theta_{k,t+1}\mid \theta_t, l_{k,t}, \theta_P} (\eta_{k,t} + E [\theta_{k,t+1} \mid \theta_t, l_{k,t}, \theta_P] \mid \theta_t, l_{k,t}, \theta_P, t),$$

because $p_{\theta_{k,t+1}\mid \theta_t, l_{k,t}, \theta_P}$ is known once $p_{\theta}$ is known.
Anchoring Skills in an Interpretable Metric

- It is common in the empirical literature on child schooling and investment and on value added models for test scores to measure capabilities – “ability” – by test scores.
- However, test scores are arbitrarily scaled.
- Any monotonic function of a test score is a test score.
- To gain a better understanding of the relative importance of cognitive and noncognitive skills and their interactions and the relative importance of investments at different stages of the life cycle, it is important to anchor skills in a common scale.
### Table 13: Testing Whether the Treatment Effect on Indices Based on the Unused Measures is Zero

| Skill                     | Effect | std. error | p-value | adjusted 
|---------------------------|--------|------------|---------|----------
| **Males**                 |        |            |         |          |
| PBI Socioemotional State  | 0.209  | 0.225      | 0.179   | –         |
| YRS Academic Potential    | 0.089  | 0.124      | 0.239   | –         |
| YRS Social Development    | -0.004 | 0.221      | 0.508   | –         |
| YRS Emotional Adjustment  | -0.067 | 0.171      | 0.652   | –         |
| PBI Teacher Dependence    | -0.356 | 0.219      | 0.945   | –         |
| Joint Test (d)            |        |            |         | 0.443     |
| **Females**               |        |            |         |          |
| YRS Academic Potential    | 0.286  | 0.190      | **0.072** | 0.180    |
| PBI Socioemotional State  | 0.347  | 0.298      | 0.126   | –         |
| YRS Social Development    | 0.204  | 0.191      | 0.147   | –         |
| YRS Emotional Adjustment  | 0.152  | 0.231      | 0.258   | –         |
| PBI Teacher Dependence    | 0.181  | 0.352      | 0.306   | –         |
| Joint Test (d)            |        |            |         | 0.287     |
Table 14: Testing Whether the Unused Measures Have No Effect on Outcomes

<table>
<thead>
<tr>
<th>Outcomes</th>
<th>Unused Measures(^{(a)})</th>
<th>Indices(^{(b)})</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( p)-value(^{(c)}) adjusted(^{(d)})</td>
<td>( p)-value(^{(c)}) adjusted(^{(d)})</td>
</tr>
<tr>
<td><strong>Males</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td># of felony arrests, age 40</td>
<td>.103 (\text{--}^{(e)})</td>
<td>.250 (\text{--}^{(e)})</td>
</tr>
<tr>
<td># of adult (misd. + fel.) arrests, age 40</td>
<td>.121 –</td>
<td>.570 –</td>
</tr>
<tr>
<td># of lifetime arrests, age 40</td>
<td>.125 –</td>
<td>.550 –</td>
</tr>
<tr>
<td># of felony arrests, age 27</td>
<td>.133 –</td>
<td>.130 –</td>
</tr>
<tr>
<td># of misdemeanor arrests, age 40</td>
<td>.196 –</td>
<td>.770 –</td>
</tr>
<tr>
<td># of adult (misd. + fel.) arrests, age 27</td>
<td>.235 –</td>
<td>.490 –</td>
</tr>
<tr>
<td>CAT total, age 14</td>
<td>.345 –</td>
<td>.740 –</td>
</tr>
<tr>
<td># of misdemeanor arrests, age 27</td>
<td>.468 –</td>
<td>.890 –</td>
</tr>
<tr>
<td>Joint Test(^{(g)})</td>
<td>.161</td>
<td>.548</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Females</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>CAT total, age 8</td>
<td>\textbf{.086} .290</td>
<td>\textbf{.050} .112</td>
</tr>
<tr>
<td># of misdemeanor violent crimes, age 40</td>
<td>.301 (\text{--}^{(f)})</td>
<td>.220 (\text{--}^{(f)})</td>
</tr>
<tr>
<td># of misdemeanor violent crimes, age 27</td>
<td>.320 –</td>
<td>.210 –</td>
</tr>
<tr>
<td># of lifetime violent crimes, age 40</td>
<td>.424 –</td>
<td>.320 –</td>
</tr>
<tr>
<td>CAT total, age 14</td>
<td>.449 –</td>
<td>.400 –</td>
</tr>
<tr>
<td># of felony arrests, age 27</td>
<td>.456 –</td>
<td>.390 –</td>
</tr>
<tr>
<td># of felony arrests, age 40</td>
<td>.600 –</td>
<td>.540 –</td>
</tr>
<tr>
<td>Joint Test(^{(g)})</td>
<td>.380</td>
<td>.196</td>
</tr>
</tbody>
</table>

Heckman  The Economics/Econometrics
Digression on Direct Quartimin Procedure

- Abstract from previous notation to consider the EFA problem.
- Use general notation for factors

\[
\begin{align*}
M &= \mu + \Lambda + \Theta + U \\
\text{Observed} & \quad \text{Means} & \quad \text{Factor} & \quad \text{Factors} & \quad \text{Uniqueness} \\
\text{Responses} & \quad (P \times 1) & \quad (P \times 1) & \quad (P \times L) & \quad (L \times 1)
\end{align*}
\]

- Components of \(U\) mutually uncorrelated
Notation for Rotation

- For expositional purposes only: Normalize each component of $\Theta$ to have unit variance.

$$\sum_M = \Lambda \Phi_\Theta \Lambda' + \Psi_U$$

$$\Phi_\Theta = \text{Cov}(\Theta) \quad \Psi_U = \text{Cov}(U)$$

- $\Psi_U$: diagonal
Steps in EFA

- Estimate $\Omega = \Lambda \Phi \Theta \Lambda'$ ("extraction").
- Estimate $\Lambda$ and $\Phi \Theta$ ("rotation").
Thurstone’s “Perfect Simple Structure”: Dedicated measures

- Facilitates interpretability of the factor system.
- 3 Factors \((L = 3)\), 7 Measures \((P = 7)\)

\[
\Lambda = \begin{bmatrix}
1 & 0 & 0 \\
1 & 0 & 0 \\
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
0 & 0 & 1 \\
\end{bmatrix}
\]

Each measure loaded on a single factor.
• Measure of complexity \( Q(\Lambda) \)
• Penalizes Departures from Perfect Simple Structure.
• Normalize the data in \( M \) to have unit variance.
• Define \( A: \Omega = AA' \)
  \( A \) assumed to have full column rank

\[
\Lambda = AT^{-1}
\]
\[
\Phi = TT'
\]
Oblique Factor Analysis

- Min $Q(\Lambda)$ s.t. $\text{Diag}(TT^\prime) = I$.
- General Criterion used in the literature:

$$Q(\Lambda) = (1 - k) \sum_{i=1}^{P} \sum_{j=1}^{P} \sum_{l \neq j, l = 1}^{L} \lambda_{ij}^2 \lambda_{il}^2 + k \sum_{j=1}^{L} \sum_{i=1}^{P} \sum_{i \neq l, l = 1}^{P} \lambda_{ij}^2 \lambda_{lj}^2.$$ 

Row Complexity \hspace{2cm} Column Complexity

- Direct Quartimin: $k = 0$.
- If $Q(\Lambda) = 0$ and $k = 0$, Thurstone’s model a has perfect simple structure.
Alternative Approach Based on Loss Functions (Jennrich, 2004)

\[ Q(\Lambda) = \sum_i \sum_j h(|\lambda_{ij}|) \]

Component Loss Criterion (CLC)

Thm: Jennrich (2004)

*If there is an oblique rotation \( \tilde{\Lambda} \) of \( \Lambda \) that has a perfect simple structure, and if \( h \) is a concave and nondecreasing, then \( \tilde{\Lambda} \) minimizes \( Q(\Lambda) \) over all oblique rotations of \( \Lambda \). Moreover if \( h \) is strictly concave any minimizer must have a perfect simple structure.\]
Relationship of CLC to Direct Quartimin

- Direct quartimin does not have CLC structure.
- Yet if the corresponding criterion for direct quartimin has $Q(\Lambda) = 0$, we also obtain perfect simple structure.
Other Approaches

Application of EFA and CFA to Our Data
Application of EFA in this Paper

- We obtain measures based on standard EFA procedures described in the psychological literature (for reviews, see Tabachnick and Fidell, 2001, Thompson, 2004, and Costello and Osborne, 2005). We implement a stepwise procedure to obtain a stable set of dedicated measures based on the following rules:
  1. Apply quartimin rotation and obtain factor loadings.
  2. Exclude measures that have two or more loadings in any columns greater than 0.4 (the cross-loading problem).
  3. Exclude measures that do not have loadings at least .6 or higher for at least one gender (the weak loading problem).

- The procedure stops when the set of measures converge, that is, we obtain a stable set of measures based on the iterative application of rules 1 to 3.
Table 15: Factor Loadings of a Three-Factor Model After Oblique Rotation

<table>
<thead>
<tr>
<th></th>
<th>Males</th>
<th>Females</th>
<th>Pooled</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stanford Binet, age 7</td>
<td>0.666 (.099)</td>
<td>-0.030 (.099)</td>
<td>0.123 (.116)</td>
</tr>
<tr>
<td>Stanford Binet, age 8</td>
<td>0.700 (.086)</td>
<td>-0.104 (.084)</td>
<td>0.222 (.106)</td>
</tr>
<tr>
<td>Stanford Binet, age 9</td>
<td>0.925 (.063)</td>
<td>0.070 (.047)</td>
<td>0.008 (.049)</td>
</tr>
<tr>
<td>Externalizing Behavior</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disrupts classroom procedures</td>
<td>-0.084 (.072)</td>
<td>0.782 (.065)</td>
<td>0.176 (.088)</td>
</tr>
<tr>
<td>Swears or uses obscene words</td>
<td>-0.154 (.076)</td>
<td>0.732 (.075)</td>
<td>0.235 (.094)</td>
</tr>
<tr>
<td>Steals</td>
<td>-0.010 (.134)</td>
<td>0.371 (.134)</td>
<td>0.119 (.150)</td>
</tr>
<tr>
<td>Lying or cheating</td>
<td>-0.155 (.095)</td>
<td>0.569 (.101)</td>
<td>0.332 (.115)</td>
</tr>
<tr>
<td>Influences others toward troublemaking</td>
<td>-0.037 (.058)</td>
<td>0.927 (.043)</td>
<td>-0.028 (.066)</td>
</tr>
<tr>
<td>Aggressive toward peers</td>
<td>0.260 (.077)</td>
<td>0.841 (.065)</td>
<td>-0.145 (.071)</td>
</tr>
<tr>
<td>Teases or provokes students</td>
<td>0.053 (.078)</td>
<td>0.834 (.063)</td>
<td>-0.059 (.086)</td>
</tr>
<tr>
<td>Academic Motivation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shows Initiative</td>
<td>0.076 (.051)</td>
<td>0.065 (.042)</td>
<td>0.910 (.047)</td>
</tr>
<tr>
<td>Alert and interested in school work</td>
<td>0.082 (.051)</td>
<td>0.069 (.055)</td>
<td>0.895 (.054)</td>
</tr>
<tr>
<td>Hesitant to try, or gives up easily</td>
<td>0.049 (.088)</td>
<td>0.195 (.100)</td>
<td>0.664 (.093)</td>
</tr>
<tr>
<td>Sample size</td>
<td>59</td>
<td>37</td>
<td>96</td>
</tr>
</tbody>
</table>

Notes: Factor loadings based on the exploratory factor analysis with direct quartimin rotation are shown. Maximum likelihood asymptotic standard errors are in parentheses. Factor loadings relating factors to corresponding potential dedicated measures are in bold.
Confirmatory Factor Analysis

- Follow Gorsuch (2003) and Thompson (2004), and derive a fully dedicated system as described by equations (14)–(16).
- This procedure is an application of confirmatory factor analysis (CFA).
- In our application, it produces an interpretable system that could have been picked using an “operationalization” approach.
Estimation Procedure

- Can estimate the joint system by MLE.
- A simpler more intuitive procedure estimates the model in three stages.
  1. Estimate the measurement system.
  2. Estimate skills for each participant.
  3. Estimate the relationship between participant skills and life-time outcomes.
- Links the method to a form of matching on unobservables or, more accurately, imperfectly measured variables.
- We compute \( p \)-values using the bootstrap.
- We draw \( B = 1000 \) bootstrap samples.
Three-step Estimation

1. Estimate the factor model using measurement system (14)–(16).

2. Use the measures and factor loadings estimated in the first step to compute a vector of factor scores for each participant $i$:

$$M_i = \varphi \theta_i + \eta_i$$  \hspace{1cm} (55)

- $\varphi$ represents a matrix of the factor loadings estimated in first step.
- $M_i$ is the vector of stacked measures for participant $i$ subtracting the intercepts $\nu^j_{m_i}$ of equation (14).
- $E(\eta_i) = 0$, $\eta_i \perp \theta_i$, $\text{Cov}(\eta_i, \eta_i) = \Omega$. 
Three-step Estimation (Cont.)

• Unbiased estimator of the factor (Bartlett, 1937):

\[ \theta_{S,i} = L'M_i = (\varphi'\Omega^{-1}\varphi)^{-1}\varphi'\Omega^{-1}M_i. \]

• Can adjust for estimated \( \varphi \)

3 Bias-correction Procedure:

i Use of factor scores instead of the true factors to estimate the outcome equation (17) generates biased estimates of outcome coefficients \( \alpha \).

ii From the factor analysis of the measurements, we can identify the measurement error and the variance of the components.

iii In this fashion we correct the bias.
Return to main text
The results from both procedures are in close agreement, although $p$-values from the maximum likelihood procedure are generally lower.
**Figure 6: Decompositions of Treatment Effects, Factor Scores versus MLE**

- **# of misdemeanor violent crimes, age 27 (-)**
  - **SCORE**: 0.099
  - **MLE**: 0.020
  - **Females**: 0.079
  - **Males**: 0.072

- **# of felony arrests, age 27 (-)**
  - **SCORE**: 0.120
  - **MLE**: 0.048
  - **Females**: 0.114
  - **Males**: 0.072

- **# of misdemeanor violent crimes, age 40 (-)**
  - **SCORE**: 0.066
  - **MLE**: 0.020
  - **Females**: 0.071
  - **Males**: 0.085

- **# of felony arrests, age 40 (-)**
  - **SCORE**: 0.050
  - **MLE**: 0.025
  - **Females**: 0.056
  - **Males**: 0.079

- **# of misdemeanor arrests, age 27 (-)**
  - **SCORE**: 0.071
  - **MLE**: 0.091
  - **Females**: 0.071
  - **Males**: 0.085

- **# of felony arrests, age 27 (-)**
  - **SCORE**: 0.071
  - **MLE**: 0.085
  - **Females**: 0.071
  - **Males**: 0.085

- **# of misdemeanor arrests, age 40 (-)**
  - **SCORE**: 0.136
  - **MLE**: 0.132
  - **Females**: 0.088
  - **Males**: 0.067

- **# of felony arrests, age 40 (-)**
  - **SCORE**: 0.056
  - **MLE**: 0.079
  - **Females**: 0.056
  - **Males**: 0.079

Legend:
- Cognition
- Externalizing Behavior
- Academic Motivation
- Other Factors
Analyzing Treatment Effects for ABC

1. Introduce challenges, programs, and goals; survey main findings
2. Describe data
   - Experimental data
   - Multiple sources of auxiliary non-experimental data to forecast life-cycle gains
3. Present each methodological segment
   - **First**: Define treatment effects and parameters of interest
   - **Intermediate step**: Estimate treatment effects; multiple hypothesis testing and counts of positive (and significant) treatment effects
   - **Third**: Cost-benefit analysis
4. Empirical estimates
Methodological challenges and practical issues arise:

1. Many outcomes: multiple hypothesis testing challenges
2. Different forms of attrition and non-compliance
3. Substitution bias: many control children attended other preschools
4. Intermittent data collection——*interpolation*
5. Forecast and monetize life-cycle gains——*extrapolation*
Challenges

- **Comprehensive solution to multiple hypothesis testing:**
  - Cost-benefit analysis (CBA)
  - We want to understand the contribution of each component to the overall CBA
    - Multiple hypothesis testing (Lehmann and Romano, 2005; Romano and Shaikh, 2006)
      - But often arbitrary blocks are used to perform step-down
    - Counts of positive (and significant) treatment effects
      - Do not weigh the *intensity of the effect* on each outcome
We study two high-quality randomized controlled trials:
  - The Carolina Abecedarian Project (ABC)
  - The Carolina Approach to Responsive Education (CARE)

ABC and CARE are very similar programs
  - They were implemented in the 1970s and early 1980s in the same center
  - They include two phases of randomly assigned treatment:
    1. Child Age: 0 to 5
       → Gave children center-based childcare
       → CARE: additional treatment group receiving home visits only (family education treatment)
    2. School Age: 5 to 8
       → Home visits
Preview of Results: Treatment Effects

**Figure 1:** Proportion of Outcomes with a Positive Treatment Effect

→ Strengthen when accounting for substitution bias
Preview of Results: Cost-Benefit Analysis

- Monetize multiple dimensions of life-cycle costs and benefits
  → Costs: program, alternative preschool, education
  → Benefits: reduced special education; parental income; labor income; judicial, incarceration, and victimization costs; health expenditures; quality-adjusted life years

<table>
<thead>
<tr>
<th></th>
<th>Benefit-Cost Ratio</th>
<th>Internal Rate of Return</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Std. Error</td>
</tr>
<tr>
<td>Females</td>
<td>1.56</td>
<td>1.42</td>
</tr>
<tr>
<td>Males</td>
<td>6.91</td>
<td>4.43</td>
</tr>
<tr>
<td>Pooled</td>
<td>4.30</td>
<td>2.15</td>
</tr>
</tbody>
</table>
Importance of Accounting for Long-Term Effects

Figure 2: Benefit-Cost Ratio When Accounting for Benefits at Different Ages

- The pooled benefit-cost ratio is 0.59 at age 5, 2.69 at age 30, and 4.3 at age 79
Data
• Treatment group (59); Control group (57)
• 70% of control-group children attended alternative preschools
• Data on non-compliers available up to age 8: analyses accounting for these indicate insensitivity
• Account for attrition using inverse probability weighting → Based on conditional independence (Horvitz and Thompson, 1952)
Auxiliary Data Sources

- Auxiliary data used to construct life-cycle profiles:
  1. Spans the life cycle
  2. Years of birth of the auxiliary sample match those of ABC
  3. Common support in predictors of outcome

Auxiliary Sources for Interpolation and Extrapolation

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Transfer Income</td>
<td>cNLSY</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>NLSY79; PSID</td>
</tr>
<tr>
<td>Subject Income</td>
<td>cNLSY</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>NLSY79; PSID</td>
</tr>
<tr>
<td>Health</td>
<td></td>
<td></td>
<td>PSID; MEPS; MCBS; HRS</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crime</td>
<td></td>
<td></td>
<td>NCDPS; NVS; UCR</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Methodology
Evaluation Framework

- \( Y^1(\omega) \): treatment outcome
- \( Y^0_H(\omega) \): control outcome staying at home
- \( Y^0_C(\omega) \): control outcome in an alternative preschool
- \( D = 1 \) indicates desire to participate of the program
- \( R|D = 1 \) random variable; randomization in or out treatment
Evaluation Framework

- Assume discrete temporal dimension; \( T \) periods
- \( V \): proportion of months in alternative preschool
- Crude summary of likely more complex dynamics

\[
V(\omega) := \frac{\# \{ t : Y_0^H(t, \omega) - Y_0^C(t, \omega) \leq 0 \}}{T}
\]  

(1)

- Counterfactual outcomes:
- Assume \( Y_0^H(t, \omega) = Y_0^H(\omega) ; Y_0^C(t, \omega) = Y_0^C(\omega) \)

\[
Y^0(\omega) := [1 - V(\omega)] Y_0^H(\omega) + V(\omega) Y_0^C(\omega)
\]  

(2)
Control-Group Substitution, ABC

Figure 3: Months in Alternative Preschools, ABC Control Group
Control-Group Substitution, CARE

Figure 4: Months in Alternative Preschools, CARE

- Cumulative Density Function
- Proportion of Months in Preschool from Ages 0 to 5

- Control Family Education Treatment

Heckman CBA Analysis
Evaluation Framework

- Possible approaches:
  1. Multiple values for $V$ (possibly continuous in the limit)
  2. Or restrict to binary values of $V$: ($V = 0, V > 0$)
- Consider a Roy-type setting (binary discrete choice)
- In our samples, treatment is preferred to either non-treatment outcomes:
  \[
  \Pr \left( Y^1(\omega) \geq \max (Y^0_H(\omega), Y^0_C(\omega)) \mid D = 1 \right) = 1 \tag{3}
  \]
- Could instead use utilities over outcomes–e.g., $U(Y^1(\omega))$
- Could add costs as well.
- Various methods identify and estimate the marginal distributions of $Y^0_H, Y^0_C$
- Problematic to utilize in a small sample setting
- Ideally, construct counterfactual $Y^0_C(v, \omega)$ for $v \in [0, 1]$
- Difficult in small samples
Alternative Evaluation Counterfactuals

- **Standard version:**
  \[
  \Delta := \mathbb{E}_\Omega \left[ Y^1 - \max(Y^0_H, Y^0_C) \mid D = 1 \right] \tag{4}
  \]

- Evaluate relative to no control-group alternatives take-up
  \[
  \Delta (V = 0) := \mathbb{E}_\Omega \left[ Y^1 (v) - Y^0 (v) \mid V = 0, D = 1 \right] \tag{5}
  \]

- Estimator:
  \[
  \hat{\Delta} (V = 0) := \hat{\mathbb{E}} [Y \mid D = 1, R = 1, V \in [0, \eta]] \\
  - \hat{\mathbb{E}} [Y \mid D = 1, R = 0, V \in [0, \eta]] \tag{6}
  \]
  with \( \eta \to 0 \)

- \( \Delta (V > 0) \) analogously defined and estimated for \( V > 0 \).
Multiple Hypothesis Testing

- Many outcomes
  (i) One possible procedure: step-down; blocks often arbitrary
  (ii) Another possible procedure: combine all the treatment effects in a single statistic
  - \( G \): index set for groups of outcomes
  - \( O_g \): group of outcomes; \( g \in G \); cardinality \( \#O_g \)
  - \( F_{j,g}(y_r) \): marginal distribution of outcome \( j \) in \( O_g \); treatment group \( r \in \{0, 1\} \)
  - \( \Delta_{j,g} \): treatment effect associated with outcome \( j \) in \( O_g \)

\[
\Delta_{j,g} := \mathbb{E}_\Omega \left[ Y_{j,g}^1 - \max (Y_{j,g,H}^0, Y_{j,g,C}^0) \mid D = 1 \right]
\]  

(7)
Counting Positive Treatment Effects (Assumes Ability to Rank All Outcomes)

- Null hypotheses of interest:
  \[ H_0 : F_{j,g}^0 = F_{j,g}^1, \quad \forall j \in O^g \]  
  \[ (8) \]

- In practice, we test:
  \[ H_0 : \Delta_{j,g} = 0, \quad \forall j \in O^g \]

- Statistic:
  \[ T_g = \sum_{j=1}^{\#O^g} 1 \left[ \hat{\Delta}_{j,g} > 0 \right] \]  
  \[ (9) \]

- Test analogous hypotheses and define analogous statistic for positive and significant treatment effects
Cost-Benefit Methodology

- Monetize lifetime social costs and benefits generated by the programs: income, health, education, and crime
- Multiple challenges
  1. Intermittent data collection
  2. Collection only up to age 34
  3. Attrition in later follow-ups
- Interpolation and extrapolation using multiple sources of auxiliary data
- Two statistics of interest: **internal rate of return** and **benefit-cost ratio**
- Provide standard errors and sensitivity analysis to choices of parameters
Link to
Earnings Projections
Monetizing Crime Outcomes

- **Two elements**
  - Account for costs and benefits up to age 35
  - Extrapolate thereafter: similar methodology as used for income

- **Data on arrests**
  - Administrative data up to age 35
  - Self-reported up to age 30

- **Auxiliary datasets:**
  - National Victimization Survey (NVS)
  - Uniform Crime Reports (UCR)
  - North Carolina Department of Public Safety (NCDPS)

- **Account for victimization inflation**
  - Use NVS and the UCR to create a ratio of victims to arrests
Extrapolation of Health Outcomes

- Future America Model (FAM)
  → Non-experimental data to provide estimates of medical expenditure and QALYs (Goldman et al., 2015)
- First-order Markov process
  → Estimate probability of an individual transitioning into a health state
  → Monetize each health state based on SES characteristics
- Feed income projections and simulate the estimated outcomes using Monte-Carlo simulations
  → Model incorporates subjects’ data on heart disease, cancer, hypertension, smoking, marriage, divorce, insurance type
- We estimate medical expenditure for ages 16 to 79 and account for the improvement to quality-of-life (QALY)
<table>
<thead>
<tr>
<th></th>
<th>Preschool</th>
<th>School Age</th>
<th>Young Adult</th>
<th>Mid-30s</th>
<th>Midlife</th>
<th>Post-Retirement</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Program Costs</strong></td>
<td>Nutrition; medical costs; education</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Other Center-Based Education</strong></td>
<td>Education; subsidies</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td>Elementary to high school; grade retention; special education</td>
<td>High school; GED; vocational; college</td>
<td>Rest of education history</td>
<td></td>
<td></td>
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</tr>
<tr>
<td><strong>Parental Income</strong></td>
<td>Total labor income</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Welfare Income</strong></td>
<td>Total transfers received from government</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Subject Income</strong></td>
<td>Total labor income</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Health</strong></td>
<td>Medical expenditures; quality-adjusted life years</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td><strong>Crime</strong></td>
<td>Prison; justice system; victimization costs</td>
<td>Prediction and imputation of crime sentence and justice system costs</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Empirical Estimates
Summary of Treatment Effects

- Males and Females: majority of outcomes display positive treatment effect → More than 30% are individually statistically significant at 10% level
- Females:
  - Positive effects on outcomes related to cognitive skills and education
  - Once control-group substitution is accounted for, results strengthen
- Males:
  - Positive effects on outcomes related to labor market performance and health
  - Results are weaker with respect to step-down correction
- Gender difference in impacted outcomes generates difference in benefit-cost calculation
  → Outcomes impacted for males have higher monetary value
Table 2: ABC and CARE Females, Selected Outcomes

<table>
<thead>
<tr>
<th>Variable</th>
<th>Age</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. IQ Test</td>
<td>12</td>
<td>8.259</td>
<td>10.139</td>
<td>8.457</td>
<td>7.891</td>
<td>8.167</td>
<td>7.217</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.013)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.026)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>Years of Edu.</td>
<td>30</td>
<td>1.474</td>
<td>1.266</td>
<td>1.967</td>
<td>1.289</td>
<td>1.244</td>
<td>0.992</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.026)</td>
<td>(0.066)</td>
<td>(0.066)</td>
<td>(0.211)</td>
<td>(0.039)</td>
<td>(0.053)</td>
</tr>
<tr>
<td>Public-Transfer Income</td>
<td>30</td>
<td>-884</td>
<td>-192</td>
<td>-980</td>
<td>-290</td>
<td>-839</td>
<td>-667</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.053)</td>
<td>(0.395)</td>
<td>(0.053)</td>
<td>(0.316)</td>
<td>(0.118)</td>
<td>(0.158)</td>
</tr>
<tr>
<td>Total Years Incarcerated</td>
<td>30</td>
<td>-0.020</td>
<td>-0.012</td>
<td></td>
<td>-0.031</td>
<td>-0.018</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.039)</td>
<td>(0.171)</td>
<td></td>
<td>(0.039)</td>
<td>(0.053)</td>
<td></td>
</tr>
<tr>
<td>Diabetes</td>
<td>Mid-30s</td>
<td>-0.053</td>
<td>-0.036</td>
<td></td>
<td>-0.074</td>
<td>-0.075</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.079)</td>
<td>(0.132)</td>
<td></td>
<td>(0.066)</td>
<td>(0.079)</td>
<td></td>
</tr>
</tbody>
</table>

(1) $\mathbb{E}_\Omega [Y^1(\omega) - Y^0(\omega)|D = 1]$
(2) $\mathbb{E}_\Omega [Y^1(\omega) - Y^0(\omega)|X, D = 1]$
(3) $\mathbb{E}_\Omega [Y^1(\omega)] - \mathbb{E}_\Omega [Y^0(\nu, \omega)|V = 0, D = 1]$
(4) $\mathbb{E}_\Omega [Y^1(\nu, \omega) - Y^0(\nu, \omega)|V = 0, D = 1]$
(5) $\mathbb{E}_\Omega [Y^1(\omega)] - \mathbb{E}_\Omega [Y^0(\nu, \omega)|V > 0, D = 1]$
(6) $\mathbb{E}_\Omega [Y^1(\nu, \omega) - Y^0(\nu, \omega)|V > 0, D = 1]$
### Table 3: ABC and CARE Males, Selected Outcomes

<table>
<thead>
<tr>
<th>Variable</th>
<th>Age</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of Edu.</td>
<td>30</td>
<td>1.046</td>
<td>1.232</td>
<td>1.643</td>
<td>1.698</td>
<td>0.792</td>
<td>0.729</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.092)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>Labor Income</td>
<td>30</td>
<td>10,070</td>
<td>19,026</td>
<td>10,973</td>
<td>17,564</td>
<td>9,675</td>
<td>16,433</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.079)</td>
<td>(0.079)</td>
<td>(0.053)</td>
<td>(0.105)</td>
<td>(0.105)</td>
<td>(0.092)</td>
</tr>
<tr>
<td>Total Misdemeanor Arrests</td>
<td>Mid-30s</td>
<td>-0.686</td>
<td>-0.578</td>
<td>-0.823</td>
<td>-0.544</td>
<td>-0.621</td>
<td>-0.400</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.039)</td>
<td>(0.118)</td>
<td>(0.105)</td>
<td>(0.237)</td>
<td>(0.053)</td>
<td>(0.171)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.132)</td>
<td>(0.092)</td>
<td>(0.013)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Vitamin D Deficiency</td>
<td>Mid-30s</td>
<td>-0.280</td>
<td>-0.230</td>
<td>-0.480</td>
<td>-0.502</td>
<td>-0.202</td>
<td>-0.255</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.079)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.053)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Self-reported drug user</td>
<td>Mid-30s</td>
<td>-0.357</td>
<td>-0.534</td>
<td>-0.691</td>
<td>-0.814</td>
<td>-0.191</td>
<td>-0.241</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.0105)</td>
<td>(0.053)</td>
<td></td>
</tr>
</tbody>
</table>

(1) $\mathbb{E}_\Omega[Y^1(\omega) - Y^0(\omega)|D = 1]$

(2) $\mathbb{E}_\Omega[Y^1(\omega) - Y^0(\omega)|X, D = 1]$

(3) $\mathbb{E}_\Omega[Y^1(\omega)] - \mathbb{E}_\Omega[Y^0(\omega)|V = 0, D = 1]$

(4) $\mathbb{E}_\Omega[Y^1(\nu, \omega) - Y^0(\nu, \omega)|V = 0, D = 1]$

(5) $\mathbb{E}_\Omega[Y^1(\omega)] - \mathbb{E}_\Omega[Y^0(\nu, \omega)|V > 0, D = 1]$

(6) $\mathbb{E}_\Omega[Y^1(\nu, \omega) - Y^0(\nu, \omega)|V > 0, D = 1]$
Figure 5: Proportion of Outcomes with a Positive Treatment Effect

Parents' Income
HOME Scores
IQ Scores
Achievement Scores
Mental Health
Education
Employment and Income
Crime

Females  Males  +/- s.e.
Figure 6: Proportion of Outcomes with a Positive Treatment Effect
Figure 7: Proportion of Outcomes with a Positive and Significant Treatment Effect, at 10% Level
Figure 8: Proportion of Outcomes with a Positive Treatment Effect Fixing Control Group to No Alternative Preschool
We estimate the following:

- Net Present Value (NPV) in 2014 USD, discounted at 3% per year until birth
- Internal Rate of Return (IRR)
- Benefit-Cost Ratio (B/C)

Standard errors are presented in parentheses and obtained using bootstrapping:

- 200 resamples of ABC
- 200 resamples of auxiliary data

Point estimates in bold are significant at the 10% level in a one-sided test.
## Results and Sensitivity Analysis

### Table 4: Benefit-Cost Ratio and Rate of Return

<table>
<thead>
<tr>
<th>Removed Component</th>
<th>Females</th>
<th></th>
<th>Males</th>
<th></th>
<th>Pooled</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NPV</td>
<td>IRR</td>
<td>B/C</td>
<td>NPV</td>
<td>IRR</td>
<td>B/C</td>
</tr>
<tr>
<td>None</td>
<td>0.05</td>
<td>1.56</td>
<td>0.25</td>
<td>6.91</td>
<td>0.16</td>
<td>4.30</td>
</tr>
<tr>
<td>Parental Income</td>
<td>61,862</td>
<td>0.03</td>
<td>0.91</td>
<td>121,132</td>
<td>0.12</td>
<td>5.64</td>
</tr>
<tr>
<td>Subject QALY</td>
<td>6,998</td>
<td>0.05</td>
<td>1.49</td>
<td>26,800</td>
<td>0.25</td>
<td>6.63</td>
</tr>
<tr>
<td>Subject Labor Income</td>
<td>63,237</td>
<td>0.02</td>
<td>0.90</td>
<td>138,003</td>
<td>0.25</td>
<td>5.46</td>
</tr>
<tr>
<td>Subject Transfer Income</td>
<td>-13,472</td>
<td>0.06</td>
<td>1.71</td>
<td>-1,317</td>
<td>0.25</td>
<td>6.93</td>
</tr>
<tr>
<td>Medical Expenditures</td>
<td>21,178</td>
<td>0.05</td>
<td>1.34</td>
<td>37,148</td>
<td>0.24</td>
<td>6.52</td>
</tr>
<tr>
<td>Control Contamination</td>
<td>28,146</td>
<td>0.04</td>
<td>1.27</td>
<td>27,917</td>
<td>0.18</td>
<td>6.62</td>
</tr>
<tr>
<td>Education Costs</td>
<td>-36,617</td>
<td>0.07</td>
<td>1.95</td>
<td>7,292</td>
<td>0.23</td>
<td>6.84</td>
</tr>
<tr>
<td>Crime Costs</td>
<td>17,127</td>
<td>0.05</td>
<td>1.38</td>
<td>299,361</td>
<td>0.21</td>
<td>3.76</td>
</tr>
</tbody>
</table>

Note: Values in parentheses are standard errors.
Appendix
First-Phase Treatment, ABC

- First-phase Treatment, ABC: one control group and one treatment group
  - Control group (57 children):
    1. Iron-fortified formula and monthly supply of diapers, first 15 months of life
  - Treatment group (59 children):
    1. Iron-fortified formula and monthly supply of diapers, first 15 months of life
    2. Breakfast, lunch, and afternoon snack
    3. Medical care from nurses, supervised by a doctor
    4. Center-based childcare
First-Phase Treatment, CARE

- First-phase Treatment, CARE: one control group and two treatment groups
  - Control group (23 children):
    1. Iron-fortified formula and monthly supply of diapers, first 15 months of life
  - Family education treatment group (27 children)
    1. Iron-fortified formula and monthly supply of diapers, first 15 months of life
    2. Home visits that aimed to help parents solve common problems related to child rearing
  - Center-based childcare and family education treatment group (16 children):
    1. Same as the family education treatment group
    2. Center-based childcare
Second-Phase Treatment, ABC and CARE

- For both programs: home visits from ages 5 to 8 → similar in objectives to first-phase home visits of CARE
- ABC: re-randomized at age 5 to either receive or not the home visits → 96 children were re-randomized
- CARE: participants of the two first-phase treatment groups received second-phase treatment
Both programs targeted disadvantaged children from the semi-rural communities of Chapel Hill close to the Frank Porter Graham Center (FPGC) of the University of North Carolina.

- Mothers in the last trimester of pregnancy were referred by local social service agencies and hospitals.
- Eligibility was determined by a score of 11 or more on the High-risk Index (HRI).
- Example HRI items:
  - Mother’s education level
  - Use of welfare programs
  - Father’s presence at home

Although race was not a consideration for eligibility, 98% of ABC participants and 90% of CARE participants were African-American.
Sample

- **ABC**
  - Four cohorts of children born between 1972 and 1977
  - 122 individuals recruited

- **CARE**
  - Two cohorts of children born in 1978 and 1979
  - 67 individuals recruited

- Overall, mothers in CARE were older, more educated, and had higher IQ than the mothers in ABC
We compare the ABC and CARE samples to a comparison group using a cohort of the Panel Study of Income Dynamics born in the same years as the ABC and CARE subjects (1972-1979)

ABC and CARE subjects were born to younger, less educated mothers many of whom were raising their children without the father present.
Figure 9: Average Age of Mothers at Child’s Birth

- Of Children born in 1972−1979
- Of Black Children born in 1972−1979
- ABC
- CARE

Heckman CBA Analysis
Figure 10: Average Education of Mothers at Child’s Birth

Of Children born in 1972−1979
Of Black Children born in 1972−1979
ABC CARE

Heckman CBA Analysis
Figure 11: Proportion of Fathers at Home at Child’s Birth

- Of Children born in 1972-1979
- Of Black Children born in 1972-1979
- ABC
- CARE
ABC Randomization

- First Phase: 122 children randomized to one treatment group that received center-based childcare and one control group
  - Effective sample size after randomization compromises: 116 (59 treatment, 57 control)
- Second Phase: 96 of the original children were randomized into one treatment and one control group
CARE Randomization

- **First Phase:** 67 children randomized into:
  - One treatment group that received center-based childcare and family education (16 children)
  - One treatment group that only received family education (27 children)
  - One control group (23 children)

- **Second Phase:** Children in the two treatment groups automatically received the second-phase treatment and the control group remained the same

- **No randomization compromises except death and families moving away from the study area**
ABC First-Phase Randomization Compromises

1 Left the study before data collection: We have no data at all for these subjects.

2 Death before age 5 / Moved out: We include them in estimations until data are no longer available. Thereafter, they are cases of attrition.

3 Partial treatment: We assume that they had full treatment.

4 Noncompliance to treatment: We keep the original treatment status for them for ITT estimations.

5 Crossover from control to treatment: Three children switched status from control to treatment. We keep the original treatment statuses for ITT estimations.

6 Developmental delays: We drop them because they were not eligible for the program.
1 **Not randomized in second phase:**
   - Stopped being followed-up: They are considered cases of attrition
   - Followed-up in later data collection: They are not included when calculating the treatment effects for the second phase, but are included when estimating treatment effects of the first phase on later outcomes

2 **Noncompliance in second phase:** Original treatment statuses are kept for ITT estimations
• The objectives of both ABC and CARE were to prevent “mental retardation” and develop school readiness
• The different curricula implemented across the programs and cohorts had the following goals:
  • Support language and cognitive development
  • Develop socio-emotional skills considered to enable school-readiness (e.g., task orientation)
Additional Programmatic Elements

- The ABC treatment group received
  - Daily health screenings and frequent medical check-ups
- The CARE treatment groups received
  - Home visits to help parents foment problem-solving skills
- Both ABC and CARE center-based treatment groups received
  - Transportation to and from FPGC
  - Daily nutritious food
- Both ABC and CARE control groups received
  - Iron-fortified formula until the child was 15 months old
  - Unlimited diapers until the child was 3 years old
Programmatic Elements, Second Phase

- Same treatment in ABC and CARE
- State-certified “home-school resource teachers”
- Visited the elementary school and the children’s homes twice a month to help
  - Engage the parents with the children’s academics
  - Provide one-on-one tutoring to the children
  - Parents with issues related to literacy, housing, and medical care
## Baseline Characteristics in ABC and CARE

<table>
<thead>
<tr>
<th>Variable</th>
<th>ABC Obs</th>
<th>CARE Obs</th>
<th>ABC Mean</th>
<th>CARE Mean</th>
<th>Single $H_0$</th>
<th>Multiple $H_0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>116</td>
<td>67</td>
<td>0.464</td>
<td>0.596</td>
<td>(0.060)</td>
<td>(0.110)</td>
</tr>
<tr>
<td>Birth Weight</td>
<td>114</td>
<td>64</td>
<td>7.008</td>
<td>7.139</td>
<td>(0.625)</td>
<td>(0.765)</td>
</tr>
<tr>
<td>No. Siblings in Household</td>
<td>116</td>
<td>67</td>
<td>0.632</td>
<td>0.684</td>
<td>(0.810)</td>
<td>(0.890)</td>
</tr>
<tr>
<td>Birth Year</td>
<td>116</td>
<td>67</td>
<td>1974</td>
<td>1979</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Mother’s Education</td>
<td>116</td>
<td>67</td>
<td>10.188</td>
<td>10.868</td>
<td>(0.010)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Mother’s Age</td>
<td>116</td>
<td>67</td>
<td>19.828</td>
<td>21.141</td>
<td>(0.060)</td>
<td>(0.100)</td>
</tr>
<tr>
<td>Mother’s IQ</td>
<td>116</td>
<td>67</td>
<td>84.407</td>
<td>87.164</td>
<td>(0.070)</td>
<td>(0.130)</td>
</tr>
<tr>
<td>Father at Home</td>
<td>116</td>
<td>67</td>
<td>0.283</td>
<td>0.209</td>
<td>(0.270)</td>
<td>(0.380)</td>
</tr>
</tbody>
</table>
## Programmatic Elements, First Phase Treatment

### Table 6: Elements of First Phase Treatment, ABC and CARE

<table>
<thead>
<tr>
<th></th>
<th>ABC</th>
<th>CARE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Treatment</strong></td>
<td>Center-based childcare</td>
<td>Center-based childcare and family education</td>
</tr>
<tr>
<td><strong>Center-based Childcare</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intensity</td>
<td>6.5–9.75 hours a day for 50 weeks per year</td>
<td>6.5–9.75 hours a day for 50 weeks per year</td>
</tr>
<tr>
<td>Components</td>
<td>Instruction, medical care, nutrition,</td>
<td>Instruction, medical care, nutrition,</td>
</tr>
<tr>
<td></td>
<td>social services</td>
<td>social services</td>
</tr>
<tr>
<td>Staff-to-child Ratio</td>
<td>1:3 during ages 0–1</td>
<td>1:3 during ages 0–1</td>
</tr>
<tr>
<td></td>
<td>1:4–5 during age 1–4</td>
<td>1:4–5 during age 1–4</td>
</tr>
<tr>
<td></td>
<td>1:5–6 during ages 4–5</td>
<td>1:5–6 during ages 4–5</td>
</tr>
<tr>
<td>Staff Qualifications</td>
<td>Mixed diplomas; experienced</td>
<td>Mixed diplomas; experienced</td>
</tr>
<tr>
<td><strong>Family Education</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intensity</td>
<td></td>
<td>One hour-long home visits. 2–3 per month</td>
</tr>
<tr>
<td></td>
<td></td>
<td>during ages 0–3. 1–2 per month during ages 4–5</td>
</tr>
<tr>
<td>Curriculum</td>
<td></td>
<td>Social and mental stimulation; parent-child interaction</td>
</tr>
<tr>
<td>Staff-to-child Ratio</td>
<td></td>
<td>1:1</td>
</tr>
<tr>
<td>Staff Qualifications</td>
<td></td>
<td>Home visitor training</td>
</tr>
</tbody>
</table>
### Table 7: Elements of Second Phase Treatment, ABC and CARE

<table>
<thead>
<tr>
<th></th>
<th>ABC</th>
<th>CARE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intensity</td>
<td>Every other week</td>
<td>Every other week</td>
</tr>
<tr>
<td>Components</td>
<td>Parent-teacher meetings</td>
<td>Parent-teacher meetings</td>
</tr>
<tr>
<td>Curriculum</td>
<td>Reading and math</td>
<td>Reading and math</td>
</tr>
<tr>
<td>Staff-to-child Ratio</td>
<td>1:1</td>
<td>1:1</td>
</tr>
<tr>
<td>Staff Qualifications</td>
<td>Graduate degree and training in special education</td>
<td>Graduate degree and training in special education</td>
</tr>
</tbody>
</table>
Selection into Subsidized Alternative Preschools

Figure 12: Average Months in Treatment Substitution by Subsidized Status, ABC

The chart illustrates the average months in treatment substitution by subsidized status across different ages. The x-axis represents Age 1 to Age 5, and the y-axis represents months. The bars are color-coded to indicate No Preschool Alternative, Subsidized, and Non-Subsidized categories.
Selection into Subsidized Alternative Preschools

Figure 13: Average Months in Treatment Substitution by Subsidized Status, CARE
Categorizing Outcomes as Socially Positive

- Examples of socially positive outcomes
  - Cognitive and achievement tests
  - Home environment measures
  - Income
  - Employment
  - Education

- Examples of socially negative outcomes (reversed)
  - Public-transfer income
  - Risky behavior
  - Mental health issues
  - Behavioral measures
  - Health outcomes (e.g., blood pressure)
Categorizing Outcomes as Socially Positive

- Examples of outcomes that are too ambiguous to categorize
  - Number of children
  - Age at birth of first child (apart from teenage pregnancy)
  - Marriage status
  - Car ownership
  - Parenting style (authoritarian vs. progressive)
### Table 8: ABC and CARE Females, Selected Outcomes

<table>
<thead>
<tr>
<th>Variable</th>
<th>Age</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. IQ Test</td>
<td>12</td>
<td>8.259</td>
<td>10.139</td>
<td>8.457</td>
<td>7.891</td>
<td>8.167</td>
<td>7.217</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.026)</td>
<td>(0.000)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.053)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>Years of Edu.</td>
<td>30</td>
<td>1.474</td>
<td>1.266</td>
<td>1.967</td>
<td>1.289</td>
<td>1.244</td>
<td>0.992</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.053)</td>
<td>(0.184)</td>
<td>(0.158)</td>
<td>(0.553)</td>
<td>(0.105)</td>
<td>(0.237)</td>
</tr>
<tr>
<td>Public-Transfer Income</td>
<td>30</td>
<td>-884</td>
<td>-192</td>
<td>-980</td>
<td>-290</td>
<td>-839</td>
<td>-667</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.237)</td>
<td>(0.829)</td>
<td>(0.224)</td>
<td>(0.579)</td>
<td>(0.434)</td>
<td>(0.566)</td>
</tr>
<tr>
<td>Total Years Incarcerated</td>
<td>30</td>
<td>-0.020</td>
<td>-0.012</td>
<td></td>
<td>-0.031</td>
<td>-0.018</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.197)</td>
<td>(0.487)</td>
<td></td>
<td>(0.158)</td>
<td>(0.197)</td>
<td></td>
</tr>
<tr>
<td>Diabetes</td>
<td>Mid-30s</td>
<td>-0.053</td>
<td>-0.036</td>
<td></td>
<td>-0.074</td>
<td>-0.075</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.171)</td>
<td>(0.342)</td>
<td></td>
<td>(0.132)</td>
<td>(0.158)</td>
<td></td>
</tr>
</tbody>
</table>

(1) \( \mathbb{E}_\Omega [ Y^1(\omega) - Y^0(\omega) | D = 1 ] \)
(2) \( \mathbb{E}_\Omega [ Y^1(\omega) - Y^0(\omega) | X, D = 1 ] \)
(3) \( \mathbb{E}_\Omega [ Y^1(\omega) ] - \mathbb{E}_\Omega [ Y^0(v, \omega) | V = 0, D = 1 ] \)
(4) \( \mathbb{E}_\Omega [ Y^1(v, \omega) - Y^0(v, \omega) | V = 0, D = 1 ] \)
(5) \( \mathbb{E}_\Omega [ Y^1(\omega) ] - \mathbb{E}_\Omega [ Y^0(v, \omega) | V > 0, D = 1 ] \)
(6) \( \mathbb{E}_\Omega [ Y^1(v, \omega) - Y^0(v, \omega) | V > 0, D = 1 ] \)
### Table 9: ABC and CARE Males, Selected Outcomes

<table>
<thead>
<tr>
<th>Variable</th>
<th>Age</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of Edu.</td>
<td>30</td>
<td>1.046</td>
<td>1.232</td>
<td>1.643</td>
<td>1.698</td>
<td>0.792</td>
<td>0.729</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.026)</td>
<td>(0.026)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.171)</td>
<td>(0.342)</td>
</tr>
<tr>
<td>Labor Income</td>
<td>30</td>
<td>10,070</td>
<td>19,026</td>
<td>10,973</td>
<td>17,564</td>
<td>9,675</td>
<td>16,433</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.316)</td>
<td>(0.263)</td>
<td>(0.171)</td>
<td>(0.303)</td>
<td>(0.368)</td>
<td>(0.316)</td>
</tr>
<tr>
<td>Total Misdemeanor Arrests</td>
<td>Mid-30s</td>
<td>-0.686</td>
<td>-0.578</td>
<td>-0.823</td>
<td>-0.544</td>
<td>-0.621</td>
<td>-0.400</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.105)</td>
<td>(0.197)</td>
<td>(0.250)</td>
<td>(0.474)</td>
<td>(0.145)</td>
<td>(0.395)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.039)</td>
<td>(0.000)</td>
<td>(0.355)</td>
<td>(0.211)</td>
<td>(0.053)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Vitamin D Deficiency</td>
<td>Mid-30s</td>
<td>-0.280</td>
<td>-0.230</td>
<td>-0.480</td>
<td>-0.502</td>
<td>-0.202</td>
<td>-0.255</td>
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<tr>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.079)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.053)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Self-reported drug user</td>
<td>Mid-30s</td>
<td>-0.357</td>
<td>-0.534</td>
<td>-0.691</td>
<td>-0.814</td>
<td>-0.191</td>
<td>-0.241</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.276)</td>
<td>(0.158)</td>
<td></td>
</tr>
</tbody>
</table>

\[
(1) \, \mathbb{E}_\Omega [Y^1(\omega) - Y^0(\omega)|D = 1] \\
(2) \, \mathbb{E}_\Omega [Y^1(\omega) - Y^0(\omega)|X, D = 1] \\
(3) \, \mathbb{E}_\Omega [Y^1(\omega)] - \mathbb{E}_\Omega [Y^0(\nu, \omega)|V = 0, D = 1] \\
(4) \, \mathbb{E}_\Omega [Y^1(\nu, \omega) - Y^0(\nu, \omega)|V = 0, D = 1] \\
(5) \, \mathbb{E}_\Omega [Y^1(\omega)] - \mathbb{E}_\Omega [Y^0(\nu, \omega)|V > 0, D = 1] \\
(6) \, \mathbb{E}_\Omega [Y^1(\nu, \omega) - Y^0(\nu, \omega)|V > 0, D = 1]
\]
## Table 10: ABC and CARE Females, Roy Model Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Age</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. IQ Test</td>
<td>12</td>
<td>10.548</td>
<td>12.080</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.039)</td>
<td>(0.145)</td>
<td>(0.408)</td>
</tr>
<tr>
<td>Years of Edu.</td>
<td>30</td>
<td>3.558</td>
<td>2.179</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.105)</td>
<td>(0.158)</td>
<td>(0.316)</td>
</tr>
<tr>
<td>Public-Transfer Income</td>
<td>30</td>
<td>-1,802</td>
<td>-1,621</td>
<td>7.068</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.145)</td>
<td>(0.158)</td>
<td>(0.579)</td>
</tr>
<tr>
<td>Total Misdemeanor Arrests</td>
<td>Mid-30s</td>
<td>-3.510</td>
<td>-1.408</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.171)</td>
<td>(0.145)</td>
<td>(0.947)</td>
</tr>
<tr>
<td>Diabetes</td>
<td>Mid-30s</td>
<td>0.024</td>
<td>-0.129</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.605)</td>
<td>(0.224)</td>
<td>(0.026)</td>
</tr>
</tbody>
</table>

(1) $\mathbb{E}_\Omega \left[ Y^1 (\omega) | D = 1 \right] - \mathbb{E}_\Omega \left[ Y^0_H (\omega, v) | V = 0, D = 1 \right]$

(2) $\mathbb{E}_\Omega \left[ Y^1 (\omega) | D = 1 \right] - \mathbb{E}_\Omega \left[ Y^0_C (\omega, v) | V = 1, D = 1 \right]$

(3) Coefficient on $V$
# Treatment Effects on Males

## Table 11: ABC and CARE Males, Roy Model Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Age</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of Edu.</td>
<td>30</td>
<td>0.319</td>
<td>-0.281</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.553)</td>
<td>(0.671)</td>
<td>(0.263)</td>
</tr>
<tr>
<td>Labor Income</td>
<td>30</td>
<td>16,158</td>
<td>-2,539</td>
<td>56.523</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.105)</td>
<td>(0.632)</td>
<td>(0.342)</td>
</tr>
<tr>
<td>Total Felony Arrests</td>
<td>Mid-30s</td>
<td>0.274</td>
<td>-0.982</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.553)</td>
<td>(0.276)</td>
<td>(0.632)</td>
</tr>
<tr>
<td>Diastolic Blood Pressure (mm Hg)</td>
<td>Mid-30s</td>
<td>17.237</td>
<td>-24.473</td>
<td>-0.038</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.711)</td>
<td>(0.184)</td>
<td>(0.434)</td>
</tr>
<tr>
<td>Vitamin D Deficiency</td>
<td>Mid-30s</td>
<td>-0.817</td>
<td>-0.628</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.145)</td>
<td>(0.118)</td>
<td>(0.947)</td>
</tr>
<tr>
<td>Self-reported drug user</td>
<td>Mid-30s</td>
<td>-0.764</td>
<td>0.308</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.158)</td>
<td>(0.697)</td>
<td>(0.171)</td>
</tr>
</tbody>
</table>

(1) $\mathbb{E}_\Omega \left[ Y^1(\omega) \mid D = 1 \right] - \mathbb{E}_\Omega \left[ Y^0_H(\omega, \nu) \mid V = 0, D = 1 \right]$

(2) $\mathbb{E}_\Omega \left[ Y^1(\omega) \mid D = 1 \right] - \mathbb{E}_\Omega \left[ Y^0_C(\omega, \nu) \mid V = 1, D = 1 \right]$

(3) Coefficient on $V$

---

**Heckman**

**CBA Analysis**
Components of the CBA

We incorporate all the categories of outcomes we are able to monetize

- Program costs for treatment and control groups
- Costs of alternative preschool arrangements for the control group
- Savings due to reduced grade retention, special education
- Costs due to post-secondary schooling
- Parental income

(cont.)
Components of the CBA

- Subject labor income
- Subject public transfer income
- Medical expenditure
- QALY
- Crime
Components of the CBA

- Costs of education are estimated based on literature standards (e.g., Snyder and Dillow, 2012)
- Cognitive, noncognitive, and scholastic gains we are unable to monetize are assumed to enter into the other components of the analysis
- Educational attainment is observed up to age 30 and assumed to remain constant
Program Costs

Medical costs
- Regular check-ups by full-time pediatric fellows and nurses
- Excludes laboratory costs

Non-medical labor costs
- Salaries of classroom staff, administrative staff, and support staff (e.g., transportation providers)

Facility costs
- Rental costs, utilities, maintenance, office supplies, children’s program supplies, equipment rental, and maintenance costs

Other costs
- Costs of transportation provided by the center, nutrition, and curricular materials
### Table 12: Individual Program Costs by Group

<table>
<thead>
<tr>
<th></th>
<th>Treatment</th>
<th>Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medical*</td>
<td>$4,645</td>
<td>$888</td>
</tr>
<tr>
<td>Labor</td>
<td>$49,274</td>
<td>-</td>
</tr>
<tr>
<td>Facilities</td>
<td>$31,865</td>
<td>-</td>
</tr>
<tr>
<td>Other</td>
<td>$10,633</td>
<td>$507</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>$96,417</strong></td>
<td><strong>$1,395</strong></td>
</tr>
</tbody>
</table>

*Note: these costs are presented in 2014 USD discounted to the year in which individuals were born. * The year 1 medical cost for the control group was only for the first cohort of ABC; the control groups of subsequent cohorts received no medical care. Labor costs do not include the labor costs of medical staff.
Earnings Projections
Earnings Projections

• Key component of cost-benefit analysis
• Simplify notation: suppress $D = 1$ henceforth

$$\mathbb{E}[Y| R = r, X = x, W = w, S = s] = \phi(r, x, w, s) \quad (10)$$

• $Y$: an outcome of interest—we suppress subscript $t$ for time period
• $R$: an indicator for participation in treatment (given $D = 1$)
• $X$: observed set of variables, possibly affected by treatment
• $W$: pre-program variables
• $S$: an indicator equal to 1 if data is ABC, 0 if auxiliary
**Earnings Projections**

**Assumption 1:** Common support between auxiliary datasets and the analysis sample

\[
\text{sup} \left( X \mid S = 1 \right) \subseteq \text{sup} \left( X \mid S = 0 \right)
\]

**Assumption 2:** Effect of treatment is captured by \( X \); \( Y \) is (mean) independent of \( R \) conditional on \( S, X, W \)

\[
\mathbb{E} \left[ Y \mid R = r, X = x, W = w, S = s \right] = \mathbb{E} \left[ Y \mid X = x_r, W = w, S = s \right]
\]

- \( Y := (R) Y^1 + (1 − R) Y^0 \); \( Y^r := Y \mid R = r \)
- \( x^r \): vector drawn from the distribution \( X \mid R = r \)
- \( X \): can include proxies; factors for latent skills; lagged values of \( Y \)
Let * indicate that a random variable is unobserved

- **Auxiliary Dataset,** $S = 0$: $(Y, X, W, R^*)$
- **Analysis Sample,** $S = 1$: $(Y^*, X, W, R)$

**Assumption 3:** $Y$ is independent of $S$ conditional on $X, W, R$

\[
E[Y^*|R = r, X = x, W = w, S = 1] = E[Y|R^* = r, X = x, W = w, S = 0] \text{ for } r = 0, 1
\]
Earnings Projections

We identify $\mathbb{E}[Y^r \mid S = 1]$ as follows:

$$\mathbb{E}[Y^r \mid S = 1]$$

$$= \int \mathbb{E}[Y^r \mid X = x, W = w, S = 1] f_{X,W|S=1}(x, w) dx dw$$

$$= \int \mathbb{E}[Y \mid X = x, W = w, S = 1, R = r] f_{X,W|S=1,R=r}(x, w) dx dw$$

$$= \int \mathbb{E}[Y \mid X = x, W = w, S = 0, R = r] f_{X,W|S=1,R=r}(x, w) dx dw$$

$$= \int \mathbb{E}[Y^r \mid X = x^r, W = w, S = 0] f_{X,W|S=1,R=r}(x^r, w) dx^r dw$$
Attrition

- Let $A = 0$ denote missing adult outcomes affected by treatment used in forecasting, and $A = 1$ denote otherwise
- We allow for $W$ to include post-treatment variables when accounting for attrition

**Assumption 4:** $X$ is independent of $A$ conditional on $R$ and $W$

$$X \perp \! \! \! \! \! \! \perp A \mid (R, W)$$
\[ \mathbb{E} [Y^r \mid S = 1] \]
\[ = \int \mathbb{E} [Y \mid X = x^r, W = w, S = 0] f_{X,W \mid S=1,R=r}(x^r, w) dx^r dw \]
\[ = \int \mathbb{E} [Y \mid X = x^r, W = w, S = 0] f_{X \mid S=1,W=w,R=r}(x^r) \]
\[ \quad \cdot f_{W \mid R=r}(w) dx^r dw \]
\[ = \int \mathbb{E} [Y \mid X = x^r, W = w, S = 0] f_{X \mid S=1,W=w,R=r,A=1}(x^r) \]
\[ \quad \cdot f_{W \mid R=r,A=1}(w \mid R = r, A = 1)P(A = 1 \mid R = r) \]
\[ \quad \cdot P(A = 1 \mid R = r, W = w) \]
Account for forecasting errors

**Assumption 5:** Errors additively separable:

\[ Y = \Psi (R, X, W, S) + \varepsilon \]  

(11)

- \( \varepsilon \): forecasting error
- How? Add back to projections residuals drawn with replacement within bootstraps
Practical Issues in Implementing Early Childhood Programs
Part IVE

James J. Heckman
University of Chicago

CeMMAP Masterclass
University College of London
June 23, 2016
Practical Issues

A. Whom to target?
B. With what programs?
C. Who should provide the programs?
D. Who should pay for them?
E. Issues of compliance.
Whom to target?

i. Returns highest for disadvantaged who do not get substantial early investment.

ii. What is the proper measure of disadvantage? Is it poverty? Measures of childhood home life?

iii. Evidence suggests that the quality of parenting is the key.

iv. *Parenting* is the scarce resource.

v. Not always closely linked to family income or even parental education.
With what programs?

i. Programs that target the early years seem to have the greatest promise.

ii. Nurse Family Partnership Program / Abecedarian / Perry

iii. Home visits affect the lives of the parents, create a permanent change in the home environment.

iv. Programs that build character and motivation — not just cognition — are the most effective.

v. Programs that promote nutrition and health.

vi. Quality programs; Low quality programs can harm children.
Who should provide the programs?

i. Respect the sanctity of early family life.

ii. Respect cultural diversity.

iii. Create a base of common skills and traits but do so within culturally diverse settings.

iv. Engage private industry and other social groups that
   a. Draw in private resources.
   b. Create community support.
   c. Represent diverse points of view.
Who should pay for them?

i. Can make programs universal to avoid stigmatization.
ii. Offer a sliding fee schedule to avoid deadweight losses.
iii. Mobilize private resources to support the subsidy.
Issues of compliance.

i. Many successful programs change the values and motivation of the child.

ii. This may run counter to the values of parents.

iii. There may be serious tension between the need of child and the acceptance of intervention by the parent.

iv. Then there is a basic conflict between values of society (as it seeks to develop the potential of the child) and the values of the family.
Think Globally

Extracted from: “The Scandinavian Fantasy: The Sources of Intergenerational Mobility in Denmark and the U.S.”

Part IVF

James J. Heckman
The University of Chicago

CeMMAP Masterclass
University College of London
June 23, 2016
Extracted from:

“The Scandinavian Fantasy: The Sources of Intergenerational Mobility in Denmark and the U.S.”

by Rasmus Landersø and James J. Heckman (2016)
Table 1: IGE estimates with different income measures Denmark and the U.S.

<table>
<thead>
<tr>
<th></th>
<th>Gross income excl. public transfers</th>
<th>Gross income incl. public transfers</th>
<th>Wage earnings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Denmark</td>
<td>(2) U.S.</td>
<td>(3) Denmark</td>
</tr>
<tr>
<td></td>
<td>0.352***</td>
<td>0.312***</td>
<td>0.271***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.055)</td>
<td>(0.003)</td>
</tr>
</tbody>
</table>

Note: Table shows coefficients ($\beta_{IGE}$) and standard errors from regressions on parental log of income on child’s log of income for Denmark and the U.S. For Denmark, we use full population register data for children born in 1973-1975 and for the U.S. we use PSID data children born in 1972-1978. For Denmark, parental income is measured as 9 year average from child’s seventh to fifteenth year and child’s income is measured at age 35-37, 36-38, and 37-39 for the 1975, 1974, and 1973 cohort, respectively. For the U.S., parental income is measured as 9 year average from child’s 7th to 15th year and child’s income is measured as last year income at ages 34-41, 33-40, 32-39, 31-38, 30-37, 29-36, and 28-35 for the 1972, 1973, 1974, 1975, 1976, 1977 and 1978 cohort, respectively.
Table 1: IGE estimates with different income measures Denmark and the U.S., cont’d

<table>
<thead>
<tr>
<th>Wage earnings and public transfers</th>
<th>Net-of-tax total gross income</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Denmark</td>
</tr>
<tr>
<td></td>
<td>(7)</td>
</tr>
<tr>
<td></td>
<td>U.S.</td>
</tr>
<tr>
<td></td>
<td>(8)</td>
</tr>
<tr>
<td></td>
<td>Denmark</td>
</tr>
<tr>
<td></td>
<td>(9)</td>
</tr>
<tr>
<td>0.063***</td>
<td>0.419***</td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.058)</td>
</tr>
<tr>
<td>0.221***</td>
<td>(0.003)</td>
</tr>
</tbody>
</table>

Note: Table shows coefficients ($\beta^{IGE}$) and standard errors from regressions on parental log of income on child’s log of income for Denmark and the U.S. For Denmark, we use full population register data for children born in 1973-1975 and for the U.S. we use PSID data children born in 1972-1978. For Denmark, parental income is measured as 9 year average from child’s seventh to fifteenth year and child’s income is measured at age 35-37, 36-38, and 37-39 for the 1975, 1974, and 1973 cohort, respectively. For the U.S., parental income is measured as 9 year average from child’s 7th to 15th year and child's income is measured as last year income at ages 34-41, 33-40, 32-39, 31-38, 30-37, 29-36, and 28-35 for the 1972, 1973, 1974, 1975, 1976, 1977 and 1978 cohort, respectively.
**Figure 1: Local Intergenerational Income-Elasticity in Denmark: Total Gross Income**

**Denmark**

(a) Excluding public transfers  
(b) Including public transfers

Note: Figures show estimated Intergenerational Income-Elasticities of wage income plus public transfers for Denmark (a, b) and the U.S. (c, d).
**Figure 1:** Local Intergenerational Income-Elasticity in the U.S.: Total Gross Income, cont.

(c) Excluding public transfers  
(d) Including public transfers

**U.S.**

*Note:* Figures show estimated Intergenerational Income-Elasticities of wage income plus public transfers for Denmark (a, b) and the U.S. (c, d).
Figure 2: Local Intergenerational Income-Elasticity in Denmark and the U.S.

**Denmark**

(a) Wage earnings

(b) Wage earnings and transfers

Note: Figures show estimated Intergenerational Income-Elasticities of wage income plus public transfers for Denmark (a, b, c) and the U.S. (d, e).
Figure 2: Local Intergenerational Income-Elasticity in Denmark and the U.S., cont.

Denmark
(c) Net-of-tax total gross income

Note: Figures show estimated Intergenerational Income-Elasticities of wage income plus public transfers for Denmark (a, b, c) and the U.S. (d, e).
Table 2: Regression coefficients for high school completion on parental resources by different conditioning sets

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
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</tr>
</thead>
<tbody>
<tr>
<td><strong>U.S., High school completion</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parental permanent wage income age 3-15</td>
<td>0.033***</td>
<td>0.023**</td>
<td>0.017*</td>
<td>0.006</td>
</tr>
<tr>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.007)</td>
<td></td>
</tr>
<tr>
<td>Parental wealth (net assets) age 15</td>
<td>0.020***</td>
<td>0.018***</td>
<td>0.015***</td>
<td>0.012***</td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td><strong>Denmark, High school completion</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parental permanent wage income age 3-15</td>
<td>0.066***</td>
<td>0.050***</td>
<td>0.045***</td>
<td>0.002</td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Parental wealth (net assets) age 15</td>
<td>0.037***</td>
<td>0.025***</td>
<td>0.023***</td>
<td>0.002</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td><strong>Difference in slope: U.S.-Denmark</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>∆ Parental permanent wage income age 3-15</td>
<td>-0.033</td>
<td>-0.027</td>
<td>-0.028</td>
<td>0.004</td>
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<tr>
<td>p-value</td>
<td>0.001</td>
<td>0.001</td>
<td>&lt;0.001</td>
<td>0.583</td>
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<tr>
<td>∆ Parental wealth (net assets) age</td>
<td>-0.017</td>
<td>-0.007</td>
<td>-0.008</td>
<td>0.010</td>
</tr>
<tr>
<td>p-value</td>
<td>&lt;0.001</td>
<td>0.027</td>
<td>0.001</td>
<td>0.002</td>
</tr>
</tbody>
</table>

**Residualing by:**

- \( \theta^C \), \( \theta^{NC} \)
- Family background
- School characteristics

Note: Table shows regression coefficients of parental permanent wage income and wealth on children’s highschool completion and college attendance while gradually increasing conditioning set with skills, family background and school characteristics. Table constructed using data from the CNSLY for the U.S. / administrative register data on the full cohort born in 1987 for Denmark. The table shows p-values from tests of equal slope-coefficients against a two-sided alternative.
Table 2: Regression coefficients for college attendance on parental resources by different conditioning sets, cont.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
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<tbody>
<tr>
<td><strong>U.S., College attendance</strong></td>
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<td></td>
<td></td>
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<tr>
<td>Parental permanent wage income age 3-15</td>
<td>0.063***</td>
<td>0.041***</td>
<td>0.035***</td>
<td>0.019**</td>
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<tr>
<td></td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.009)</td>
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<tr>
<td>Parental wealth (net assets) age 15</td>
<td>0.022***</td>
<td>0.019***</td>
<td>0.010**</td>
<td>0.008**</td>
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<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.003)</td>
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<tr>
<td><strong>Denmark College attendance</strong></td>
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<tr>
<td>Parental permanent wage income age 3-15</td>
<td>0.061***</td>
<td>0.043***</td>
<td>0.037***</td>
<td>0.011**</td>
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<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
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<tr>
<td>Parental wealth (net assets) age 15</td>
<td>0.034***</td>
<td>0.018***</td>
<td>0.015***</td>
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<tr>
<td><strong>Difference in slope: U.S.-Denmark</strong></td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>Δ Parental permanent wage income age 3-15</td>
<td>0.002</td>
<td>-0.002</td>
<td>-0.002</td>
<td>0.008</td>
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<td>p-value</td>
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<td>0.774</td>
<td>0.848</td>
<td>0.400</td>
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<td>Δ Parental wealth (net assets) age</td>
<td>-0.012</td>
<td>0.001</td>
<td>-0.005</td>
<td>0.007</td>
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<td>p-value</td>
<td>&lt;0.001</td>
<td>0.998</td>
<td>0.134</td>
<td>0.058</td>
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</table>

Residualing by: $\theta^C, \theta^{NC}$

Family background

School characteristics

Note: Table shows regression coefficients of parental permanent wage income and wealth on children’s highschool completion and college attendance while gradually increasing conditioning set with skills, family background and school characteristics. Table constructed using data from the CNSLY for the U.S. / administrative register data on the full cohort born in 1987 for Denmark. The table shows p-values from tests of equal slope-coefficients against a two-sided alternative.
Table 3: Regression coefficients for high school completion and college attendance on parental resources using different conditioning sets

<table>
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<tr>
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<td></td>
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<tr>
<td>Parental permanent wage income age 3-15</td>
<td>0.1650***</td>
<td>0.1280***</td>
<td>0.1005***</td>
<td>0.1434***</td>
<td>0.0687+</td>
<td>0.0803*</td>
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<td>Parental wealth (net assets) age 15</td>
<td>0.2006***</td>
<td>0.1678</td>
<td>0.1438***</td>
<td>0.1340***</td>
<td>0.1368***</td>
<td>0.0980**</td>
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<td>(0.0349)</td>
<td>(0.0381)</td>
<td>(0.0352)</td>
<td>(0.0343)</td>
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<td>(0.0366)</td>
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<td><strong>Denmark, High school completion</strong></td>
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<tr>
<td>Parental permanent wage income age 3-15</td>
<td>0.2743***</td>
<td>0.2126***</td>
<td>0.1978***</td>
<td>0.2518***</td>
<td>0.1693**</td>
<td>0.0377***</td>
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<td></td>
<td>(0.0076)</td>
<td>(0.0092)</td>
<td>(0.0082)</td>
<td>(0.0077)</td>
<td>(0.0090)</td>
<td>(0.0049)</td>
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<td>Parental wealth (net assets) age 15</td>
<td>0.2363***</td>
<td>0.1661***</td>
<td>0.1849***</td>
<td>0.2261***</td>
<td>0.1507***</td>
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<td>(0.0089)</td>
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<td>(0.0085)</td>
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<td>∆ Parental permanent wage income age 3-15</td>
<td>-0.1093</td>
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<td>-0.0973</td>
<td>-0.1084</td>
<td>-0.1006</td>
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<td>p-value</td>
<td>0.002</td>
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<td>0.009</td>
<td>0.002</td>
<td>0.008</td>
<td>0.250</td>
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<td>∆ Parental wealth (net assets) age</td>
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<td>p-value</td>
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<td>0.258</td>
<td>0.009</td>
<td>0.701</td>
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### Table 3: Regression coefficients for high school completion and college attendance on parental resources using different conditioning sets, cont’d

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<tr>
<td><strong>U.S., High school completion</strong></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Parental permanent wage income age 3-15</td>
<td>0.3757***</td>
<td>0.2566***</td>
<td>0.2466***</td>
<td>0.3069***</td>
<td>0.1876***</td>
<td>0.1645***</td>
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<tr>
<td></td>
<td>(0.0390)</td>
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<td>(0.0408)</td>
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<td>(0.0422)</td>
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<tr>
<td>Parental wealth (net assets) age 15</td>
<td>0.3152***</td>
<td>0.2497***</td>
<td>0.2287***</td>
<td>0.2506***</td>
<td>0.2134***</td>
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<tr>
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<td>(0.0388)</td>
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<td>(0.0411)</td>
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<tr>
<td><strong>U.S., College attendance</strong></td>
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<td></td>
</tr>
<tr>
<td>Parental permanent wage income age 3-15</td>
<td>0.3549***</td>
<td>0.2443</td>
<td>0.1976***</td>
<td>0.2745***</td>
<td>0.1713***</td>
<td>0.1424***</td>
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<tr>
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<td>(0.0100)</td>
<td>(0.0095)</td>
<td>(0.0090)</td>
<td>(0.0086)</td>
<td>(0.0101)</td>
<td>(0.0069)</td>
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<tr>
<td>Parental wealth (net assets) age 15</td>
<td>0.2176***</td>
<td>0.1355***</td>
<td>0.1384***</td>
<td>0.2058***</td>
<td>0.2158***</td>
<td>-0.0081</td>
</tr>
<tr>
<td></td>
<td>(0.0090)</td>
<td>(0.0080)</td>
<td>(0.0084)</td>
<td>(0.0084)</td>
<td>(0.0089)</td>
<td>(0.0081)</td>
</tr>
<tr>
<td>Δ Parental permanent wage income age 3-15</td>
<td>0.0208</td>
<td>0.0123</td>
<td>0.0490</td>
<td>0.0324</td>
<td>0.0163</td>
<td>0.0221</td>
</tr>
<tr>
<td>p-value</td>
<td>0.610</td>
<td>0.814</td>
<td>0.241</td>
<td>0.416</td>
<td>0.718</td>
<td>0.605</td>
</tr>
<tr>
<td>Δ Parental wealth (net assets) age</td>
<td>0.0976</td>
<td>0.1142</td>
<td>0.0903</td>
<td>0.0448</td>
<td>0.1082</td>
<td>0.0262</td>
</tr>
<tr>
<td>p-value</td>
<td>0.014</td>
<td>0.023</td>
<td>0.025</td>
<td>0.254</td>
<td>0.016</td>
<td>0.532</td>
</tr>
</tbody>
</table>

**Residualing by:**

- \( \theta^C \), \( \theta^{NC} \)  
- Family background  
- School characteristics

**Extract**
Figure 3: High school completion and college attendance by parental income and wealth after residualizing by cognitive and noncognitive skills

(a) High school completion, U.S.   (b) High school completion, Denmark
Figure 3: High school completion and college attendance by parental income and wealth after residualizing by cognitive and noncognitive skills, cont’d

(c) College Attendance, U.S.  
(d) College Attendance, Denmark