Investing in Children’s Skills: Equilibrium Analysis of Social Interactions and Parental Investments

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Motivation

• **How do social interactions affect the dynamics of skill formation?**
  ▶ Peer effects (effect of friends’ achievements on a child’s outcome)
  ▶ Parental investments respond to the child’s social interactions

• **Many policies have lasting effects on peers’ composition**
  ▶ Examples: school busing policies, re-drawing school’s district boundaries, etc
  ▶ Size of the policy matters (no. of children)
    - School composition is changed
    - Children make new friends
    - Parental investments endogenously respond to changes in peers
This Paper

- **Dynamic equilibrium model of child development and social interactions**
  - Children grow up in different *environments* (peers composition, neighborhood quality, school quality)
  - Endogenous peer network formation and parental investments
  - Technology of skill formation
  - Equilibrium effects within each environment:
    - Individual return of investing is affected by other parents’ investments (through children’s social interactions)
    - Explain part of developmental gaps between different environments

- Preview of Results:
  - Moving many children to better environments:
    - Important dynamic equilibrium effects
      - Receiving children: up to -10% SD skills at age 16
    - Heterogeneous effects due to endogenous formation of new peers
This Paper

• **Dynamic equilibrium model of child development and social interactions**
  - Children grow up in different environments
    (peers composition, neighborhood quality, school quality)
  - Endogenous peer network formation and parental investments
  - Technology of skill formation
  - Equilibrium effects within each environment:
    - Individual return of investing is affected by other parents’ investments
      (through children’s social interactions)
    - Explain part of developmental gaps between different environments

• **Preview of Results:** Moving many children to better environment:
  - Important dynamic equilibrium effects
    - Receiving children: up to -10% SD skills at age 16
  - Heterogeneous effects due to endogenous formation of new peers
Data and Empirical Evidence
Data

• The National Longitudinal Study of Adolescent Health (Add Health)

• Representative for US schools in 94-95
  ▶ 144 public and private schools
  ▶ In-school survey: 90,118 adolescents in grades 7-12
  ▶ In-home survey: 20,745 subsample of In-school survey
  ▶ Contextual information about Census Tract (e.g.: median household income)

• Friendships nomination
  ▶ Friendship network within school roster

• Measures for adolescents achievements (skills)
  ▶ Peabody Picture Vocabulary Test (PPVT)
  ▶ Math, Science, English and History Grades

• Measures for parental investments (In-home survey)
Summary of Empirical Evidence

1. Homophily-bias in friendship formation
   - Race
   - Skills (New Fact)

2. Parental investments respond to peer compositions (New Fact)
   - Empirical challenge: peer groups are formed endogenously
   - I exploit within-school/across-cohorts variation in peer composition (see Hoxby, 2000)
     - Shifts in the *choice set* from which children can select their friends
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2. Parental investments respond to peer compositions (New Fact)
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What’s the effect on child development of changes in peer composition?
   - To answer this question, I need a model with:
     1. Endogenous formation of new peer groups
     2. Parents respond to peer changes
       - Equilibrium effects of other parents’ investments on a child development
The Model
The Model

- Children will be between 13 and 16 years old

- Different environments $e \in \{1, \ldots, E\}$:
  - Populated by $N_e$ families
  - Neighborhood quality $d$
  - School quality $s$

- Families are formed by one parent and one child
  - Heterogeneous in many dimensions: skills, race, income

1. **Children:**
   - Select their peers based on their observed characteristics and skills

2. **Parents:**
   - Take children’s decision as given
   - Invest their time to foster their children’s skills

- **Equilibrium:** Parental investments have to be consistent with each other
  (Equilibrium concept: Markovian Equilibrium)
Technology of Skill Formation

\[ h_{i,t+1} = h_{i,t}^{\alpha_1} \left[ \alpha_2 \left( I_{i,t} \right)^{\alpha_3} + (1 - \alpha_2) \left( \overline{H}_{i,t} \right)^{\alpha_3} \right]^{\frac{\alpha_4}{\alpha_3}} \cdot e^{A_d + A_s + A_t + \eta_{i,t+1}} \]

- \( h_{i,t+1} \): Next-period stock of skills
- \( h_{i,t} \): Current stock of skills
- \( I_{i,t} \): Parental investments
- \( L_{i,j,t} \): Indicator of friendship (\( = 1 \) if \( i \) and \( j \) are friends)
- Peer effects: \( \overline{H}_{i,t} = \frac{1}{\sum_{j=1, j \neq i}^{H} L_{i,j,t} \sum_{j=1, j \neq i}^{H} L_{i,j,t} h_{j,t}} \)
- \( A_d \) neighborhood effect
- \( A_s \) school effect
- \( A_t \) trend
- \( \eta_{i,t+1} \) skills shock
- Age of children: \( t \in \{13, \ldots, 16\} \)

Empirical Specification
Timeline

Child’s skills \((h_{i,t})\) formed

Peer groups formed

Child’s skills \((h_{i,t+1})\) formed

Parental Investment Decision

Child’s Friendships Decision
Estimation
### Sample Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Child’s Age</td>
<td>15.65</td>
<td>1.74</td>
</tr>
<tr>
<td>Fraction black</td>
<td>0.16</td>
<td>0.37</td>
</tr>
<tr>
<td>Fraction hispanic</td>
<td>0.17</td>
<td>0.38</td>
</tr>
<tr>
<td>Fraction white</td>
<td>0.67</td>
<td>0.47</td>
</tr>
<tr>
<td>N of reported friends (In-School)</td>
<td>6.98</td>
<td>3.28</td>
</tr>
</tbody>
</table>

#### Schools characteristics:

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>School size</td>
<td>1,042</td>
<td>629</td>
</tr>
<tr>
<td>Cohort size</td>
<td>261</td>
<td>156</td>
</tr>
</tbody>
</table>

#### Measures for skills:

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>PPVT</td>
<td>64.26</td>
<td>11.14</td>
</tr>
<tr>
<td>English</td>
<td>2.83</td>
<td>0.98</td>
</tr>
<tr>
<td>Math</td>
<td>2.72</td>
<td>1.03</td>
</tr>
<tr>
<td>History</td>
<td>2.86</td>
<td>1.01</td>
</tr>
<tr>
<td>Science</td>
<td>2.82</td>
<td>1.01</td>
</tr>
</tbody>
</table>

#### Family’s characteristics:

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Income ($ 1994)</td>
<td>42,844</td>
<td>27,724</td>
</tr>
<tr>
<td>Mother’s education</td>
<td>13.13</td>
<td>2.35</td>
</tr>
</tbody>
</table>

#### No of Obs

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>In-School Survey</td>
<td>90,118</td>
</tr>
<tr>
<td>In-Home Survey</td>
<td>14,267</td>
</tr>
</tbody>
</table>
Structural Estimation

• Estimator: Simulated Method of Moments (SMM)

• Dynamic latent factor model (skills and investments are unobserved)
  ▶ Cunha et al. (2010), Agostinelli and Wiswall (2016)

• Moments selection and identification:
  ▶ Indirect Inference:
    - Elasticities of parental investments w.r.t. peers’ skills
    - Autocorrelation in skill formation and parental investments
  ▶ Distribution of skills by age between environments
  ▶ Moments on homophily-bias in friendship formation
  ▶ School and neighborhood valued added
Indirect Infecence: Auxiliary Model

- I want to identify the peer effects on parental investments
- 2SLS estimator (both in data and simulated data):

(Second Stage) \[ \Delta_s I_{i,t} = \gamma_1 \Delta_s \ln h_{i,t} + \gamma_2 \Delta_s \ln H_{i,t} + \Delta_s X_i' \gamma_3 + \Delta_s \gamma_t + \Delta_s \epsilon_{i,t} \]

(First Stage) \[ \Delta_s \ln H_{i,t} = \beta_1 \Delta_s \ln h_{i,t} + \beta_2 \Delta_s Z_{i,t} + \Delta_s X_i' \beta_3 + \Delta_s \beta_t + \Delta_s u_{i,t} \]

- \( \Delta_s \): within-school transformation
- \( \beta_2 \) identifies degree of homophily in friendships formation
- \( \gamma_2 \) identifies parents-peers complementarities in skill formation
- \( \Delta_s Z_{i,t} \): within-school/between-cohorts variation in % same-race children
  - Common IV in peer effects literature (see Hoxby, 2000)
  - I allow interaction with child’s skills to account for homophily in skills
## Sample Fit: Auxiliary Regressions Coefficients

<table>
<thead>
<tr>
<th>Instrumental Variables (IV)</th>
<th>Data</th>
<th>Instrumental Variables (IV)</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peer’s Skills (Log)</td>
<td>0.720(0.354) [0.026,1.414]</td>
<td>0.895</td>
<td></td>
</tr>
<tr>
<td>First Stage</td>
<td></td>
<td>First Stage</td>
<td></td>
</tr>
<tr>
<td>$Z_{1,i,t}$ (Minorities Children)</td>
<td>-0.104(0.052) [-0.206,-0.002]</td>
<td>-0.127</td>
<td></td>
</tr>
<tr>
<td>$Z_{2,i,t}$ (White Children)</td>
<td>0.082(0.037) [0.009,0.155]</td>
<td>0.105</td>
<td></td>
</tr>
<tr>
<td>F-Stat Excl. Instruments</td>
<td>11.78</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P-value</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Each regression includes age and school fixed effects and controls for family characteristics. Standard errors are clustered at school level.
Structural Estimates

• Technology:
  ▶ CES complementarity parameter = 0.944 (s.e. 0.087)
    - Almost perfect substitute
  ▶ Self-Productivity = 0.744 (s.e. 0.068)
    - ↑ 1% current skills ⇒ ↑ 0.74% next period skills (elasticity)

• Peer-Network Formation:
  ▶ A white child with low-skills (first quintile skills distribution)
    - 2.5 times more likely to befriend a same-race child
    - 2 times more likely to befriend a same-skill child
  ▶ A black child with low-skills (first quintile skills distribution)
    - 4 times more likely to befriend a same-race child
    - 2 times more likely to befriend a same-skill child
Larger-scale policy

• Moving children at age 13 from low-income environment
  ▶ First quartile of skill distribution
  ▶ From 1% to 30% of population of the receiving neighborhood
  ▶ Median family income \( \approx 25k \) (in 2017 dollars)
  ▶ Racial composition: 10% white, 43% hispanic, 47% black

• Receiving high-income environment
  ▶ Median family income \( \approx 100k \) (in 2017 dollars)
  ▶ Racial composition: 84% white, 10% hispanic, 6% black

• Caveats:
  ▶ No endogenous response of changing environment
  ▶ Neighborhood and School quality are policy invariant
Treatment Effect by Fraction of Moved Eligible Children

![Graph showing the relationship between the percentage of children who are moved and final log-skill outcomes at age 16.](image-url)
Aggregate Effects on Skill Distribution

Change in Aggregate Mean Skills

Change in Aggregate SD Skills
Why are receiving children negatively affected?
Expected Peers for Receiving Children (10% Policy)

Probability Distribution of Peers' Skills for Receiving Children at age 14

- Baseline
- Counterfactual
Expected Peers for Receiving Children (10% Policy)
Are effects on receiving children heterogeneous?

- Evidences on differential (stronger) peer effects on **minorities** (Hoxby (2000); Angrist and Lang (2004); Imberman, Kugler and Sacerdote (2012))

- Is it a story of endogenous social interactions?
Effects on Receiving Children by Race

- Stronger policy effects for minorities
Conclusions

• I built and estimated a model of child development and social interactions

• Estimated model replicates previous findings on childhood exposure effects
  ▶ Treatment effects are not informative for large-scale policies

• Large-scale policies
  ▶ Dynamic-equilibrium effects are key for policy predictions
  ▶ Heterogeneous effects based on endogenous formation of new peer groups
## Panel A: Effects on Children’s Log-Skills (Mean)

<table>
<thead>
<tr>
<th>Age</th>
<th>Counterfactual (Equilibrium)</th>
<th>Counterfactual (No Equilibrium)</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>14</td>
<td>+0.09</td>
<td>+0.04</td>
</tr>
<tr>
<td>15</td>
<td>+0.16</td>
<td>+0.10</td>
</tr>
<tr>
<td>16</td>
<td>+0.31</td>
<td>+0.26</td>
</tr>
</tbody>
</table>

## Panel B: Effects on Parent’s Investment Decision (Mean)

<table>
<thead>
<tr>
<th>Age</th>
<th>Counterfactual (Equilibrium)</th>
<th>Counterfactual (No Equilibrium)</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>+1.63</td>
<td>-0.03</td>
</tr>
<tr>
<td>14</td>
<td>+0.62</td>
<td>-0.85</td>
</tr>
<tr>
<td>15</td>
<td>-0.42</td>
<td>-0.79</td>
</tr>
</tbody>
</table>
Expected Peers for Moved Children: Baseline vs Counterfactual

Probability Distribution of Peers' Skills for Moved Children at age Age 14

- Baseline
- Counterfactual
Are effects heterogeneous by initial skill endowment?
Heterogeneous Effects in Moved Children by Skills

![Graph showing the relationship between Child's Initial (Age 13) Skills Percentiles and Return of Policy (% Change in Skills at Age 16). There are two lines: one for TE by Skills and another for ATE. The TE by Skills line decreases as the percentiles increase, while the ATE line remains constant at 0.30.]
Latent Factor Model for Skills

- Measures for skills I use:
  - PPVT
  - Math Grades
  - Science Grades
  - English Grades
  - History Grades

- Latent factor model for some measure/proxy $m$:

$$Z_{i,t,m} = \mu_{t,m} + \lambda_{t,m} \ln h_{i,t} + \epsilon_{i,t,m}$$

  - $Z_{i,t,m}$: Observed proxy
  - $\mu_{t,m}$: Location of measure
  - $\lambda_{t,m}$: Factor loading/scale of measure
  - $\ln h_{i,t}$: Latent skills
  - $\epsilon_{i,t,m}$: Measurement error

  - $t$: Age of child
  - $\mu_{t,m}$: Location of measure
  - $\lambda_{t,m}$: Factor loading/scale of measure
Latent Factor Model for Investments

- $Z_{i,k,t} \in \{0, 1\}$ Observed measure of investments
- $p(I_{i,t})$: probability $Z_{i,k,t} = 1$ function of latent investment
- Assumptions:
  1. $p(I_{i,t}) \sim \text{Beta}(\alpha + Z_{i,k,t}, 1 + \beta - Z_{i,k,t})$
  2. $p(I_{i,t}) = \left(\frac{I_{i,t}}{\tau}\right)^{\lambda_{k,t}}$ where $\frac{I_{i,t}}{\tau}$ is fraction of invested time
- $\{I_{i,t}\}_i, \alpha, \beta, \{\lambda_{k,t}\}_k$ are identified up to normalization (scale and location)
- Look at ATUS to identify mean and variance of fraction of time invested (location and scale for latent investments)
Peer Group Formation: Black - Low Skills - Child

![Graph showing probability of link by child's skills percentiles for same race and other race children.](image)
Peer Group Formation: White - Low Skills - Child
Estimates for Initial Conditions

Panel A: Mean Initial Child’s and Mother’s Skills

<table>
<thead>
<tr>
<th>Neighborhood 1</th>
<th>Neighborhood 2</th>
<th>Neighborhood 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Child Mother</td>
<td>Child Mother</td>
<td>Child Mother</td>
</tr>
<tr>
<td>Black</td>
<td>-0.47 (0.08)</td>
<td>-0.40 (0.27)</td>
</tr>
<tr>
<td></td>
<td>-0.07 (0.15)</td>
<td>0.36 (0.25)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.49 (0.11)</td>
<td>-0.48 (0.26)</td>
</tr>
<tr>
<td></td>
<td>-0.93 (0.19)</td>
<td>-0.77 (0.19)</td>
</tr>
<tr>
<td>White</td>
<td>0.00 (0.24)</td>
<td>0.02 (0.18)</td>
</tr>
<tr>
<td></td>
<td>0.00 (0.19)</td>
<td>0.26 (0.18)</td>
</tr>
</tbody>
</table>

Panel B: Variance-Covariance Initial Child’s and Mother’s Skills

<table>
<thead>
<tr>
<th>Neighborhood 1</th>
<th>Neighborhood 2</th>
<th>Neighborhood 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Child Mother</td>
<td>Child Mother</td>
<td>Child Mother</td>
</tr>
<tr>
<td>Black</td>
<td>0.65 (0.05)</td>
<td>0.87 (0.08)</td>
</tr>
<tr>
<td></td>
<td>0.20 (0.08)</td>
<td>0.31 (0.09)</td>
</tr>
<tr>
<td></td>
<td>0.61 (0.14)</td>
<td>0.67 (0.17)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.84 (0.09)</td>
<td>1.10 (0.10)</td>
</tr>
<tr>
<td></td>
<td>0.22 (0.08)</td>
<td>0.26 (0.08)</td>
</tr>
<tr>
<td></td>
<td>1.59 (0.32)</td>
<td>1.58 (0.35)</td>
</tr>
<tr>
<td>White</td>
<td>1.00 (-)</td>
<td>1.00 (0.09)</td>
</tr>
<tr>
<td></td>
<td>0.48 (0.07)</td>
<td>0.37 (0.04)</td>
</tr>
<tr>
<td></td>
<td>1.00 (-)</td>
<td>0.74 (0.19)</td>
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### Estimates: Technology

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Child’s Skills ($\alpha_1$)</td>
<td>0.744</td>
<td>0.0682</td>
</tr>
<tr>
<td>Investments (Yearly Hours, $\alpha_2$)</td>
<td>0.009</td>
<td>0.0014</td>
</tr>
<tr>
<td>Elasticity Investment vs Peers ($\alpha_3$)</td>
<td>0.944</td>
<td>0.0270</td>
</tr>
<tr>
<td>Return to Scale ($\alpha_4$)</td>
<td>0.767</td>
<td>0.0283</td>
</tr>
<tr>
<td>Std of Shocks ($\sigma_\xi$)</td>
<td>0.700</td>
<td>0.0461</td>
</tr>
</tbody>
</table>

**Panel B: Neighborhood TFP**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant ($\gamma_{0,tfp}$)</td>
<td>-1.329</td>
<td>0.1256</td>
</tr>
<tr>
<td>Neighborhood Quality ($\gamma_{1,tfp}$)</td>
<td>0.008</td>
<td>0.0003</td>
</tr>
<tr>
<td>Age Trend ($\gamma_{2,tfp}$)</td>
<td>0.030</td>
<td>0.0008</td>
</tr>
</tbody>
</table>

**Panel C: School-Quality Effects**

<table>
<thead>
<tr>
<th>Low Income Neighborhood</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean ($\eta_{s,1}$)</td>
<td>-0.033</td>
<td>0.0330</td>
</tr>
<tr>
<td>Standard Deviation ($\sigma_{s,1}$)</td>
<td>0.262</td>
<td>0.0264</td>
</tr>
<tr>
<td>Medium Income Neighborhood</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean ($\eta_{s,2}$)</td>
<td>0.006</td>
<td>0.0277</td>
</tr>
<tr>
<td>Standard Deviation ($\sigma_{s,2}$)</td>
<td>0.244</td>
<td>0.0278</td>
</tr>
<tr>
<td>High Income Neighborhood</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean ($\eta_{s,3}$)</td>
<td>0.041</td>
<td>0.0318</td>
</tr>
<tr>
<td>Standard Deviation ($\sigma_{s,3}$)</td>
<td>0.188</td>
<td>0.0249</td>
</tr>
</tbody>
</table>
## Estimate of Preferences and Wage/Income Process

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>S.E.</th>
</tr>
</thead>
</table>

### Panel A: Preferences Parameters

- Curvature on consumption \( (\gamma_1) \) 0.786 0.0046
- Weight on Child’s Skills \( (\gamma_2) \) 0.901 0.0030
- Weight on Final Child’s Skills \( (\gamma_4) \) 2.475 0.2455
- Curvature on Child’s Skills \( (\gamma_3) \) 0.562 0.0256
- Curvature on Final Child’s Skills \( (\gamma_5) \) 0.465 0.0011

### Panel B: Parameters of Labor and Non-Labor Income

- Constant \( (\text{Wage, } \kappa_{1,0}) \) 2.750 0.0067
- Mother’s Skills \( (\text{Wage, } \kappa_{1,1}) \) 0.438 0.0048
- Constant \( (\text{Non-Labor Income, } \kappa_{2,0}) \) 9.992 0.0174
- Mother’s Skills \( (\text{Non-Labor Income, } \kappa_{2,1}) \) 1.033 0.0113
## Estimate: Child’s Utility

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant $(\delta_1)$</td>
<td>-0.246</td>
<td>0.0172</td>
</tr>
<tr>
<td>Child’s Log-Skills $(\delta_2)$</td>
<td>0.088</td>
<td>0.0048</td>
</tr>
<tr>
<td>Black $(\delta_{3,1})$</td>
<td>0.075</td>
<td>0.0023</td>
</tr>
<tr>
<td>Hispanic $(\delta_{3,2})$</td>
<td>-0.005</td>
<td>0.0001</td>
</tr>
<tr>
<td>Both Black $(\delta_{4,1})$</td>
<td>0.763</td>
<td>0.0317</td>
</tr>
<tr>
<td>Both Hispanic $(\delta_{4,2})$</td>
<td>0.701</td>
<td>0.0298</td>
</tr>
<tr>
<td>Both White $(\delta_{4,3})$</td>
<td>0.559</td>
<td>0.0475</td>
</tr>
<tr>
<td>Distance in Children’s Skills $(\delta_5)$</td>
<td>-0.038</td>
<td>0.0014</td>
</tr>
<tr>
<td>N of Children (Hundreds, $\delta_{6,1}$)</td>
<td>-0.890</td>
<td>0.0003</td>
</tr>
<tr>
<td>N of Children Squared (Hundreds, $\delta_{6,2}$)</td>
<td>0.001</td>
<td>0.0000</td>
</tr>
<tr>
<td>Distance in Children’s Skills · %White $(\delta_{6,3})$</td>
<td>-0.063</td>
<td>0.0032</td>
</tr>
<tr>
<td>Distance in Children’s Skills · %Black $(\delta_{6,4})$</td>
<td>0.042</td>
<td>0.0025</td>
</tr>
<tr>
<td>Age $(\delta_7)$</td>
<td>-0.050</td>
<td>0.0010</td>
</tr>
<tr>
<td>Additional Unobserved Heterogeneity $(\zeta_{i,j,t})$</td>
<td>Correlation with Skill Shocks</td>
<td>-0.404</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation</td>
<td>0.110</td>
</tr>
</tbody>
</table>
Dynamics of Mean Children’s Skills by Race and Neighborhood
Dynamics of Std Children’s Skills by Race and Neighborhood

- Standard Deviation of Log-Skills for Black Children living in Neighborhood 1
  - Age 13: Data, Model
  - Age 14: Data, Model
  - Age 15: Data, Model
  - Age 16: Data, Model

- Standard Deviation of Log-Skills for Hispanic Children living in Neighborhood 1
  - Age 13: Data, Model
  - Age 14: Data, Model
  - Age 15: Data, Model
  - Age 16: Data, Model

- Standard Deviation of Log-Skills for White Children living in Neighborhood 1
  - Age 13: Data, Model
  - Age 14: Data, Model
  - Age 15: Data, Model
  - Age 16: Data, Model

- Standard Deviation of Log-Skills for Black Children living in Neighborhood 2
  - Age 13: Data, Model
  - Age 14: Data, Model
  - Age 15: Data, Model
  - Age 16: Data, Model

- Standard Deviation of Log-Skills for Hispanic Children living in Neighborhood 2
  - Age 13: Data, Model
  - Age 14: Data, Model
  - Age 15: Data, Model
  - Age 16: Data, Model

- Standard Deviation of Log-Skills for White Children living in Neighborhood 2
  - Age 13: Data, Model
  - Age 14: Data, Model
  - Age 15: Data, Model
  - Age 16: Data, Model

- Standard Deviation of Log-Skills for Black Children living in Neighborhood 3
  - Age 13: Data, Model
  - Age 14: Data, Model
  - Age 15: Data, Model
  - Age 16: Data, Model

- Standard Deviation of Log-Skills for Hispanic Children living in Neighborhood 3
  - Age 13: Data, Model
  - Age 14: Data, Model
  - Age 15: Data, Model
  - Age 16: Data, Model

- Standard Deviation of Log-Skills for White Children living in Neighborhood 3
  - Age 13: Data, Model
  - Age 14: Data, Model
  - Age 15: Data, Model
  - Age 16: Data, Model
Homophily Skill Index by Skills and Neighborhood

Homophily Skills Index in Neighborhood 1

Homophily Skills Index in Neighborhood 2

Homophily Skills Index in Neighborhood 3

Return
Homophily Race Index by Race and Neighborhood

Homophily Race Index in Neighborhood 1

Homophily Race Index in Neighborhood 2

Homophily Race Index in Neighborhood 3
Expected Peers for Moved Children: Baseline vs Counterfactual
Technology of Skill Formation

\[ h_{i,t+1} = h_{i,t}^{\alpha_1} \left[ \alpha_2 \ (I_{i,t})^{\alpha_3} + \alpha_4 \ (\bar{H}_{i,t})^{\alpha_3} + \alpha_5 \ (A_s)^{\alpha_3} \right]^{\frac{\alpha_6}{\alpha_3}} \cdot A_{d,t} \cdot e^{\eta_{i,t+1}} \]

- \( \bar{H}_{i,t} \) and \( \eta_{i,t+1} \) correlated via unobserved heterogeneity in peer groups formation

- Peer effects: \( \bar{H}_{i,t} = \frac{1}{\sum_{j=1, j \neq i}^{H} L_{i,j,t}} \sum_{j=1, j \neq i}^{H} L_{i,j,t} \ h_{j,t} \)

- \( A_{d,t} \) neighborhood quality

- \( A_s \) school quality

- \( \eta_{i,t+1} \) skills shock (it is realized end of each period)
Heterogeneous Treatment Effect by Skills Receiving Children

![Graph showing the effect of skills receiving on treatment outcomes. The x-axis represents the child's initial (Age 13) skills percentiles, and the y-axis represents the return of policy (% change in skills). The graph shows a curve that peaks at around the 60th percentile and then declines.]
Latent Parental Investments and Skills

- Dynamic latent factor model (as in Del Boca et al., 2014, Cunha et al., 2010, Agostinelli and Wiswall, 2016)

1. Investments \((I_{i,t})\):
   - Gone shopping
   - Played a sport
   - Gone to a religious service
   - Gone to a movie, play, museum, concert, or sports event
   - Had a talk about a personal problem
   - Had a serious argument about your behavior
   - Talked about your school work or grades
   - Worked on a project for school
   - Talked about other things you are doing in school

1. Child’s skills \((\theta_{i,t})\):
   - Peabody Picture Vocabulary Test (PPVT)
   - Math, Science, English and History Grades
Endogenous Peer Groups Formation: Race
Endogenous Peer Groups Formation: Skills
If peers’ skills double:

\[ 16 \times (-0.01441) \times 7 \times 52 = -84 \text{ hours per year} \]

\[ 84 \times 15 = 1258 \text{ $ per year} \]
Treatment Effect by Fraction of Moved Eligible Children

Moved Children

% Children who are moved vs. Final Log-Skills (Age 16) by % of Moved Eligible Children

Receiving Children

% Children who are moved vs. Final Log-Skills (Age 16) by % of Moved Eligible Children

Remained Children

% Children who are moved vs. Final Log-Skills (Age 16) by % of Moved Eligible Children

Return
Existence of Equilibrium

- The existence proof follows the lattice programming argument (Topkis, 1998)

- The goal is preserving supermodularity in the value function (Datta, Mirman and Reffett, 2002; Datta, Mirman, Morand and Reffett, 2002; Mirman, Morand and Reffett, 2008; Datta, Reffett and Wozny, 2017)

- The supermodularity here is preserved because of the technology:

\[ h_{i,t+1} = h_{i,t}^{\alpha_1} \left[ \alpha_2 (I_{i,t})^{\alpha_3} + (1 - \alpha_2) (H_{i,t})^{\alpha_3} \right]^{\frac{\alpha_4}{\alpha_3}} \cdot e^A \]

  ▶ Technology is supermodular in \( I_{i,t} \) and \( H_{i,t} \)

  ▶ Technology is supermodular in \( h_{i,t} \) and \( H_{i,t} \)