The Effect of Private Tutoring Expenditures on Academic Performance of Middle School Students: Evidence from the Korea Education Longitudinal Study

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Motivation

- Controversies over the effectiveness of educational expenditures

  1. Public school expenditures
     - Positive: Greenwald et al. (1996); Card and Krueger (1996, JEP); Krueger (2003, EJ); Banerjee et al. (2007)
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• Controversies over the effectiveness of educational expenditures

1. Public school expenditures
   • Positive: Greenwald et al. (1996); Card and Krueger (1996, JEP); Krueger (2003, EJ); Banerjee et al. (2007)
   • Negligible: Hanushek (1986, JEL; 1997, EEPA; 2003, EJ); Betts (1996); Leuven et al. (2007)

2. Private school attendance
   • Positive: Evans and Schwab (1995, QJE); Neal (1997, JOLE)
   • Negligible: Goldhaber (1996); Figlio and Stone (1999); Altonji et al. (2005, JPE)
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2. Private school attendance
   • Positive: Evans and Schwab (1995, QJE); Neal (1997, JOLE)
   • Negligible: Goldhaber (1996); Figlio and Stone (1999); Altonji et al. (2005, JPE)

3. Private tutoring
   • Positive: Dang (2007); Dang and Rogers (2008); Ono (2007)
   • Negligible: Briggs (2001); Gurun and Millimet (2008); Kang (2007)
Obstacles in an Empirical Analysis

- Conventional specification

\[ y_{it} = \beta_0 + y_{it-1}\beta_1 + s_{it}\beta_2 + X_{it}\beta_3 + \alpha_i + u_{it} \] (1)

Empirical challenges due to endogeneity of private tutoring:

\[ \text{Cov}(s_{it}, \alpha_i + u_{it}) \neq 0 \]
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Four empirical methods

1. Instrumental variable (IV) methods
   - First-born indicator ($F_i$) as an IV for $s_{it}$.
   - A key assumption: $\text{Cov}(F_i, \alpha_i + u_{it}) = 0$. 

2. First-difference (FD) methods
   - Treat $\alpha_i$ as a fixed constant.
   - A key assumption: $\text{Cov}(s_{it} - s_{it-1}, u_{it} - u_{it-1}) = 0$. 

3. Propensity-score matching (M) methods
   - Matching a treated unit with a similar untreated unit(s).
   - Conditional Independence Assumption (CIA): $y_0 \rightarrow T \mid W$. 

4. Nonparametric bounding (NB) methods
   - Calculate estimated bounds of $\text{ATE}$ instead of point estimates.
   - Key assumptions: Monotone Treatment Response (MTR) and Monotone Treatment Selection (MTS).
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Propensity-score matching methods

- Let $t \in T = \{0, 1, 2\}$ be a treatment indicator.

- Average treatment effect on the treated (ATT):
  
  $\theta_{m,l,0} = \mathbb{E}(y_m - y_l | T = m) = \mathbb{E}(y_m | T = m) - \mathbb{E}(y_l | T = m)$

- Constructing counterfactuals:
  1. Matching under CIA:

     $\theta_{m,l,0} = \mathbb{E}(y_m - y_l | T = m, W) = \mathbb{E}(y_m | T = m, W) - \mathbb{E}(y_l | T = m, W)$

     $\quad = \mathbb{E}(y_m | T = m, W) - \mathbb{E}(y_l | T = l, W)$

  2. Calculate the propensity score

     $P_m|ml(w) = P_m|ml(T = m | T = l or T = m, W = w)$.

  3. Propensity-score matching:

     $\mathbb{E}(y_l | T = m) = \mathbb{E}[\mathbb{E}(y_l | P_m|ml(W), T = l) | T = m]$. 

Propensity-score matching methods

- Let $t \in T = \{0, 1, 2\}$ be a treatment indicator.
- Average treatment effect on the treated (ATT):
  \[
  \theta_{0}^{m,l} = E(y^m - y^l| T = m) = E(y^m| T = m) - E(y^l| T = m)
  \]
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$$
\theta_{0}^{m,l} = E(y^{m} - y^{l}| T = m) = E(y^{m}| T = m) - E(y^{l}| T = m)
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- Constructing counterfactuals:
  1. Matching under CIA:

$$
\theta_{0}^{m,l} = E(y^{m} - y^{l}| T = m, W) \\
= E(y^{m}| T = m, W) - E(y^{l}| T = m, W) \\
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     P^{m|ml}(w) = P^{m|ml}(T = m | T = l \text{ or } T = m, \ W = w).
     \]
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- Average treatment effect on the treated (ATT):
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  \theta_{0}^{m,l} = E(y^m - y^l | T = m) = E(y^m | T = m) - E(y^l | T = m)
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     = E(y^m | T = m, W) - E(y^l | T = l, W)
     \]
  2. Calculate the propensity score
     \[
     P_{m|m|l}(w) = P_{m|m|l}(T = m | T = l \text{ or } T = m, W = w).
     \]
  3. Propensity-score matching:
     \[
     E(y^l | T = m) = E[E(y^l | P_{m|m|l}(W), T = l) | T = m]
     \]
Nonparametric bounding methods

1. Let $t \in T = \{0, 1, 2\}$ be a treatment indicator.
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2. Average causal effects: $E[y_i(1) - y_i(0)]$, $E[y_i(2) - y_i(1)]$, and $E[y_i(2) - y_i(0)]$
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3. Decompose $E[y(t)]$ by

$$E[y(t)] = E[y|z = t]Pr(z = t) + E[y(t)|z \neq t]Pr(z \neq t)$$
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\[ E[y(t)] = E[y|z = t]Pr(z = t) + E[y(t)|z \neq t]Pr(z \neq t) \]

4. Given $y(t) \in [K_0, K_1]$, worst-case (WC) bounds of $E[y(t)]$

\[ E[y|z = t]Pr(z = t) + K_0 Pr(z \neq t) \leq E[y(t)] \leq E[y|z = t]Pr(z = t) + K_1 Pr(z \neq t) \]
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\[
E[y|z = t]Pr(z = t) + K_0 Pr(z \neq t) \\
\leq E[y(t)] \leq \\
E[y|z = t]Pr(z = t) + K_1 Pr(z \neq t)
\]

5. UB of \( E[y(t_m)] - E[y(t_l)] = UB \) of \( E[y(t_m)] - LB \) of \( E[y(t_l)] \)

\[
LB \ of \ E[y(t_m)] - E[y(t_l)] = LB \ of \ E[y(t_m)] - UB \ of \ E[y(t_l)]
\]
Nonparametric bounding methods

1. MTR bounds of $E[y(t)]$
   - Monotone treatment response (MTR):
     
     $$t_l < t_m \rightarrow y(t_l) \leq y(t_m)$$
Nonparametric bounding methods

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   - Monotone treatment response (MTR):
     \[ t_l < t_m \rightarrow y(t_l) \leq y(t_m) \]
   - 
     \[
     E[y|z \leq t]\Pr(z \leq t) + K_0\Pr(z > t)
     \leq E[y(t)] \leq \\
     E[y|z \geq t]\Pr(z \geq t) + K_1\Pr(z < t)
     \]
Nonparametric bounding methods

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   - Monotone treatment response (MTR):
     \[ t_i < t_m \rightarrow y(t_i) \leq y(t_m) \]
     \[ E[y|z \leq t]Pr(z \leq t) + K_0 Pr(z > t) \leq E[y(t)] \leq E[y|z \geq t]Pr(z \geq t) + K_1 Pr(z < t) \]

2. MTS bounds of $E[y(t)]$
   - Monotone treatment selection (MTS):
     \[ t_i < t_m \rightarrow E[y(t)|z = t_i] \leq E[y(t)|z = t_m] \]
Nonparametric bounding methods

1. MTR bounds of $E[y(t)]$
   - Monotone treatment response (MTR):
     \[ t_l < t_m \rightarrow y(t_l) \leq y(t_m) \]
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     \]
Nonparametric bounding methods

1. MTR+MTS bounds of $E[y(t)]$

$$
\sum_{h < t} E(y|z = h) Pr(z = h) + E(y|z = t) Pr(z \geq t) \\
\leq E[y(t)] \leq \\
\sum_{h > t} E(y|z = h) Pr(z = h) + E(y|z = t) Pr(z \leq t)
$$
Nonparametric bounding methods

1. MTR+MTS bounds of $E[y(t)]$

$$\sum_{h<t} E(y|z = h) Pr(z = h) + E(y|z = t) Pr(z \geq t) \leq E[y(t)] \leq \sum_{h>t} E(y|z = h) Pr(z = h) + E(y|z = t) Pr(z \leq t)$$

2. MIV+MTR+MTS bounds of $E[y(t)]$

- Monotone IV (MIV):

  $$u_1 < u_2 \rightarrow E[y(t)|\nu = u_1] \leq E[y(t)|\nu = u_2]$$
Nonparametric bounding methods

1. MTR+MTS bounds of $E[y(t)]$

$$
\sum_{h < t} E(y|z = h)Pr(z = h) + E(y|z = t)Pr(z \geq t) \\
\leq E[y(t)] \\
\leq \sum_{h > t} E(y|z = h)Pr(z = h) + E(y|z = t)Pr(z \leq t)
$$

2. MIV+MTR+MTS bounds of $E[y(t)]$

- Monotone IV (MIV):

  $$
  u_1 < u_2 \rightarrow E[y(t)|\nu = u_1] \leq E[y(t)|\nu = u_2]
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- MIV+MTR+MTS bounds of $E[y(t)]$
Data

• Korea Education Longitudinal Study (KELS), 2005-2007
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- A nation-wide sample of 6,908 students in grade 7.
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- A nation-wide sample of 6,908 students in grade 7.
- Main variables
  1. Outcome: Korean, English and math subject scores. Both individual subject and average scores are standardized into Z scores.
  2. Tutoring expenditures: monthly expenditures for individual subjects and three subjects as a whole.
## Table: Descriptive Statistics of the Sample

<table>
<thead>
<tr>
<th>Variables</th>
<th>Total sample</th>
<th>First-born</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Mean</td>
<td>S.D.</td>
</tr>
<tr>
<td>Average score</td>
<td>8631</td>
<td>56.2</td>
<td>20.7</td>
</tr>
<tr>
<td>Test score of Korean</td>
<td>8592</td>
<td>59.6</td>
<td>19.6</td>
</tr>
<tr>
<td>Test score of English</td>
<td>8610</td>
<td>56.4</td>
<td>25.5</td>
</tr>
<tr>
<td>Test score of math</td>
<td>8607</td>
<td>52.5</td>
<td>25.4</td>
</tr>
<tr>
<td>Total expenditures</td>
<td>8631</td>
<td>175.9</td>
<td>220.2</td>
</tr>
<tr>
<td>Any tutoring (Yes=1)</td>
<td>8631</td>
<td>0.675</td>
<td>0.469</td>
</tr>
<tr>
<td>Expenditures for Korean</td>
<td>7833</td>
<td>32.18</td>
<td>60.22</td>
</tr>
<tr>
<td>Tutoring for Korean</td>
<td>7833</td>
<td>0.423</td>
<td>0.494</td>
</tr>
<tr>
<td>Expenditures for English</td>
<td>8041</td>
<td>77.88</td>
<td>101.97</td>
</tr>
<tr>
<td>Tutoring for English</td>
<td>8041</td>
<td>0.658</td>
<td>0.475</td>
</tr>
<tr>
<td>Expenditures for math</td>
<td>8106</td>
<td>78.97</td>
<td>107.96</td>
</tr>
<tr>
<td>Tutoring for math</td>
<td>8106</td>
<td>0.658</td>
<td>0.474</td>
</tr>
<tr>
<td>Prior average score</td>
<td>8631</td>
<td>0.068</td>
<td>0.992</td>
</tr>
<tr>
<td>Prior score of Korean</td>
<td>8592</td>
<td>0.070</td>
<td>0.980</td>
</tr>
<tr>
<td>Prior score of English</td>
<td>8624</td>
<td>0.058</td>
<td>0.994</td>
</tr>
<tr>
<td>Prior score of math</td>
<td>8604</td>
<td>0.053</td>
<td>0.998</td>
</tr>
<tr>
<td>Hours of self-study</td>
<td>8631</td>
<td>5.562</td>
<td>5.141</td>
</tr>
<tr>
<td>Male (Yes=1)</td>
<td>8631</td>
<td>0.502</td>
<td>0.500</td>
</tr>
<tr>
<td>Number of children</td>
<td>8631</td>
<td>2.331</td>
<td>0.628</td>
</tr>
<tr>
<td>Handicap (Yes=1)</td>
<td>8631</td>
<td>0.034</td>
<td>0.182</td>
</tr>
<tr>
<td>First-born (Yes=1)</td>
<td>8631</td>
<td>0.452</td>
<td>0.498</td>
</tr>
</tbody>
</table>
### Table: OLS, 2SLS and FD Estimates: Average Scores

<table>
<thead>
<tr>
<th>Dep variable: Ln(Tutoring Expenditure)</th>
<th>Normalized average score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS (1)</td>
</tr>
<tr>
<td>Ln(Tutoring expenditures)</td>
<td>0.058 (0.005)**</td>
</tr>
<tr>
<td>First-born child</td>
<td>0.191 (0.032)**</td>
</tr>
<tr>
<td>Self-study</td>
<td>0.331 (0.017)**</td>
</tr>
<tr>
<td>Prior avg score</td>
<td>0.029 (0.003)**</td>
</tr>
<tr>
<td>Male</td>
<td>0.208 (0.036)**</td>
</tr>
<tr>
<td>No. of children</td>
<td>-0.102 (0.024)**</td>
</tr>
<tr>
<td>Handicapped</td>
<td>0.081 (0.079)</td>
</tr>
<tr>
<td>Intact family</td>
<td>0.220 (0.058)**</td>
</tr>
<tr>
<td>Parents’ avg age</td>
<td>0.001 (0.004)</td>
</tr>
<tr>
<td>Parents’ avg edu.</td>
<td>0.034 (0.008)**</td>
</tr>
<tr>
<td>Have religion</td>
<td>0.166 (0.031)**</td>
</tr>
<tr>
<td>Ln(income)</td>
<td>0.662 (0.029)**</td>
</tr>
<tr>
<td>Year 2007</td>
<td>0.072 (0.028)**</td>
</tr>
<tr>
<td>Intercept</td>
<td>-2.975 (0.294)**</td>
</tr>
<tr>
<td>School characteristics</td>
<td>Yes</td>
</tr>
<tr>
<td>F (IV excluded from the 2nd stage)</td>
<td>36.17</td>
</tr>
<tr>
<td>R-square</td>
<td>0.276</td>
</tr>
<tr>
<td>Number of sample</td>
<td>8,631</td>
</tr>
</tbody>
</table>
Table: OLS, 2SLS and FD Estimates: Individual Subjects

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Ln(Tutoring Expenditure)</th>
<th>Normalized test score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimation method:</td>
<td>OLS</td>
<td>2SLS</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Panel A: Korean</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(Tutoring expenditures)</td>
<td>0.026 (0.009)**</td>
<td>0.845 (0.243)****</td>
</tr>
<tr>
<td>First-born child</td>
<td>0.114 (0.025)****</td>
<td></td>
</tr>
<tr>
<td>F (IV)</td>
<td>20.91</td>
<td></td>
</tr>
<tr>
<td>Panel B: English</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(Tutoring expenditures)</td>
<td>0.084 (0.007)**</td>
<td>0.343 (0.108)****</td>
</tr>
<tr>
<td>First-born child</td>
<td>0.162 (0.026)****</td>
<td></td>
</tr>
<tr>
<td>F (IV)</td>
<td>39.76</td>
<td></td>
</tr>
<tr>
<td>Panel B: Mathematics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(Tutoring expenditures)</td>
<td>0.114 (0.008)**</td>
<td>0.389 (0.119)****</td>
</tr>
<tr>
<td>First-born child</td>
<td>0.161 (0.026)****</td>
<td></td>
</tr>
<tr>
<td>F (IV)</td>
<td>39.15</td>
<td></td>
</tr>
<tr>
<td>Outcome variables</td>
<td>Average Treatment Effects on the Treated (ATT)</td>
<td>Average Treatment Effects (ATE)</td>
</tr>
<tr>
<td>-------------------</td>
<td>-----------------------------------------------</td>
<td>----------------------------------</td>
</tr>
<tr>
<td></td>
<td>$\theta_N^{1,0}$</td>
<td>$\theta_N^{2,1}$</td>
</tr>
<tr>
<td>A. Average score of the three subjects</td>
<td>0.148** (0.031)</td>
<td>0.077* (0.033)</td>
</tr>
<tr>
<td>Elasticity:</td>
<td>0.536</td>
<td>0.341</td>
</tr>
<tr>
<td>B. Test score of Korean</td>
<td>0.088 (0.057)</td>
<td>0.078 (0.052)</td>
</tr>
<tr>
<td>Elasticity:</td>
<td>0.287</td>
<td>0.317</td>
</tr>
<tr>
<td>C. Test score of English</td>
<td>0.180** (0.032)</td>
<td>0.110** (0.038)</td>
</tr>
<tr>
<td>Elasticity:</td>
<td>0.802</td>
<td>0.563</td>
</tr>
<tr>
<td>D. Test score of Mathematics</td>
<td>0.182** (0.036)</td>
<td>0.216** (0.039)</td>
</tr>
<tr>
<td>Elasticity:</td>
<td>0.866</td>
<td>1.164</td>
</tr>
</tbody>
</table>
Table: Estimated means of $\hat{E}[y(t)]$

<table>
<thead>
<tr>
<th>Means:</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Whole</td>
</tr>
<tr>
<td>$E[y(0)]$</td>
<td>-0.392</td>
</tr>
<tr>
<td>$E[y(1)]$</td>
<td>0.107</td>
</tr>
<tr>
<td>$E[y(2)]$</td>
<td>0.481</td>
</tr>
</tbody>
</table>
Table: Estimated Bounds of the Effect

<table>
<thead>
<tr>
<th>Panel A: Average score of the three subjects</th>
<th>MTR+MTS Bounds</th>
<th>Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E[y(1) - y(0)]$</td>
<td>0.000 0.501</td>
<td>0.000 0.572</td>
</tr>
<tr>
<td>$E[y(2) - y(1)]$</td>
<td>0.000 0.367</td>
<td>0.000 0.437</td>
</tr>
<tr>
<td>$E[y(2) - y(0)]$</td>
<td>0.000 0.667</td>
<td>0.000 0.751</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Test score of Korean</th>
<th>MTR+MTS Bounds</th>
<th>Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E[y(1) - y(0)]$</td>
<td>0.000 0.055</td>
<td>0.000 0.134</td>
</tr>
<tr>
<td>$E[y(2) - y(1)]$</td>
<td>0.000 0.077</td>
<td>0.000 0.139</td>
</tr>
<tr>
<td>$E[y(2) - y(0)]$</td>
<td>0.000 0.093</td>
<td>0.000 0.169</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel A: Average score of the three subjects</th>
<th>MIV+MTR+MTS Bounds</th>
<th>Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E[y(1) - y(0)]$</td>
<td>0.000 0.482</td>
<td>0.000 0.544</td>
</tr>
<tr>
<td>$E[y(2) - y(1)]$</td>
<td>0.000 0.346</td>
<td>0.000 0.407</td>
</tr>
<tr>
<td>$E[y(2) - y(0)]$</td>
<td>0.000 0.627</td>
<td>0.000 0.702</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Test score of Korean</th>
<th>MIV+MTR+MTS Bounds</th>
<th>Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E[y(1) - y(0)]$</td>
<td>0.000 0.048</td>
<td>0.000 0.131</td>
</tr>
<tr>
<td>$E[y(2) - y(1)]$</td>
<td>0.000 0.073</td>
<td>0.000 0.135</td>
</tr>
<tr>
<td>$E[y(2) - y(0)]$</td>
<td>0.000 0.084</td>
<td>0.000 0.152</td>
</tr>
</tbody>
</table>
## Table: Estimated Bounds of the Effect

<table>
<thead>
<tr>
<th></th>
<th>LB 5 pctl</th>
<th>UB 95 pctl</th>
<th>UB 95 pctl</th>
<th>LB 5 pctl</th>
<th>UB 95 pctl</th>
<th>UB 95 pctl</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel C: Test score of English</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MTR+MTS Bounds</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$E[y(1) - y(0)]$</td>
<td>0.000</td>
<td>0.497</td>
<td>0.000</td>
<td>0.552</td>
<td>2.209</td>
<td>2.466</td>
</tr>
<tr>
<td>$E[y(2) - y(1)]$</td>
<td>0.000</td>
<td>0.396</td>
<td>0.000</td>
<td>0.456</td>
<td>2.032</td>
<td>2.333</td>
</tr>
<tr>
<td>$E[y(2) - y(0)]$</td>
<td>0.000</td>
<td>0.681</td>
<td>0.000</td>
<td>0.732</td>
<td>2.578</td>
<td>2.778</td>
</tr>
<tr>
<td>MIV+MTR+MTS Bounds</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$E[y(1) - y(0)]$</td>
<td>0.000</td>
<td>0.484</td>
<td>0.000</td>
<td>0.533</td>
<td>2.153</td>
<td>2.383</td>
</tr>
<tr>
<td>$E[y(2) - y(1)]$</td>
<td>0.000</td>
<td>0.381</td>
<td>0.000</td>
<td>0.442</td>
<td>1.956</td>
<td>2.261</td>
</tr>
<tr>
<td>$E[y(2) - y(0)]$</td>
<td>0.000</td>
<td>0.654</td>
<td>0.000</td>
<td>0.710</td>
<td>2.476</td>
<td>2.694</td>
</tr>
<tr>
<td>Panel D: Test score of Mathematics</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MTR+MTS Bounds</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$E[y(1) - y(0)]$</td>
<td>0.000</td>
<td>0.514</td>
<td>0.000</td>
<td>0.582</td>
<td>2.448</td>
<td>2.777</td>
</tr>
<tr>
<td>$E[y(2) - y(1)]$</td>
<td>0.000</td>
<td>0.431</td>
<td>0.000</td>
<td>0.482</td>
<td>2.323</td>
<td>2.603</td>
</tr>
<tr>
<td>$E[y(2) - y(0)]$</td>
<td>0.000</td>
<td>0.719</td>
<td>0.000</td>
<td>0.788</td>
<td>2.885</td>
<td>3.178</td>
</tr>
<tr>
<td>MIV+MTR+MTS Bounds</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$E[y(1) - y(0)]$</td>
<td>0.000</td>
<td>0.500</td>
<td>0.000</td>
<td>0.575</td>
<td>2.380</td>
<td>2.745</td>
</tr>
<tr>
<td>$E[y(2) - y(1)]$</td>
<td>0.000</td>
<td>0.422</td>
<td>0.000</td>
<td>0.489</td>
<td>2.275</td>
<td>2.644</td>
</tr>
<tr>
<td>$E[y(2) - y(0)]$</td>
<td>0.000</td>
<td>0.696</td>
<td>0.000</td>
<td>0.772</td>
<td>2.791</td>
<td>3.114</td>
</tr>
</tbody>
</table>
Potential Explanations

1. Monetary educational investments may not always matter.
   • Although controversial, evidence that public school resources are not an important determinant of outcomes.
   • Public mismanagement due to bureaucracies and unionization.
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1. Monetary educational investments may not always matter.
   • Although controversial, evidence that public school resources are not an important determinant of outcomes.
   • Public mismanagement due to bureaucracies and unionization.

2. Tutoring may crowd out self-study.

3. Peer pressure in parents’ peer group
   • Cultural factors in parenting (e.g., sleeping arrangement of infants).
   • Prevalence of tutoring among parents’ peers.