Child Maturation, Time-Invariant, and Time-Varying Inputs: their Relative Importance in Production of Child Human Capital

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We attempt to broaden and to redirect the standard theoretical and empirical approach in economics to the household production of human health, especially child health.

Definitions:

1. A good input could be the time spent reading to a child, while a bad input could be parental smoking near a child.
2. A good outcome could be higher reading skills, while a bad outcome could be a child’s ill-health.
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1. Children live in households with parents or adults who combine their skills with good as well as bad inputs which produce good as well as bad child health outcomes.

2. Multiple good and bad inputs can affect multiple measures of good and bad outcomes for children.

3. Households will produce child health with varying degrees of effectiveness.
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The “Best practice” household cannot increase good dimensions of child health and reduce bad dimensions by some additive amount, holding inputs constant. We estimate its TE.

Although we have panel data and compute a fixed-effects estimator, we recover the effects of time-invariant variables (such as sex, race, and parent attributes) on goods and bads in a second-stage regression.

We adjust their estimated standard errors and correct for the bias caused by weak instruments in the first stage using the bootstrap.

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The household production model (Becker, 1965; Lancaster, 1966) is traditional model. It emphasizes that relative prices and incomes, along with biological processes, condition members’ health input choices (Rosenzweig and Schultz, 1983).

The literature applying this model has either

1. regressed a single health outcome on a set of observed input choices (e.g., Todd and Wolpin, 2003; 2006) and employed instruments to account for endogeneity or
2. estimated reduced form, single output, production functions employing a common set of presumably predetermined or exogenous inputs (e.g., Blau, 1999).
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A one-sided error term reflecting random failure of inefficient households to reach the household production frontier is typically not modeled.

We include such an error here to measure technical inefficiency of households.

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Consider a household production technology where parents combine multiple good inputs, 
\[ \mathbf{x} = (x_1, \ldots, x_N) \in \mathbb{R}_+^N, \] to produce multiple good outputs, 
\[ \mathbf{y} = (y_1, \ldots, y_G) \in \mathbb{R}_+^G. \]

Production of “bad” outputs (e.g., a child’s ill-health or behavioral problems) can be appended to by defining a vector of bads, 
\[ \mathbf{b} = (b_1, \ldots, b_B) \in \mathbb{R}_+^B, \] which is produced jointly with \( \mathbf{y} \).
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Following Chambers et al. (1998), we define the output directional distance function as

\[ \overrightarrow{D}_o(x, y, b; 0, \delta_y, -\delta_b) = \sup \{ \beta : (y + \beta \delta_y, b - \beta \delta_b) \in P(x) \}, \]

where \( P(x) \) is the output set of goods and bads that can be produced with \( x \), and \( (\delta_y, \delta_b) \neq (0, 0) \) is a direction vector.

The output directional distance function increases (decreases) good (bad) outputs in the direction \( \delta_y \) (\( \delta_b \)), for a given level of observed inputs in order to move to the frontier of \( P \).
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The output directional distance function increases (decreases) good (bad) outputs in the direction $\delta_y$ ($\delta_b$), for a given level of observed inputs in order to move to the frontier of $P$. 
Output shortfalls relative to the best practice frontier are measures of technical inefficiency. The measure is equal to zero when a household is on the frontier of $P$ and greater than zero when a household is below $P$. 
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One important property of the output directional distance function is:

\[ \overrightarrow{D}_o(x, y + \alpha \delta y, b - \alpha \delta b; 0, \delta y, -\delta b) = \overrightarrow{D}_o(x, y, b; 0, \delta y, -\delta b) - \alpha, \tag{2} \]

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We failed to reject the null hypothesis that the squared and interaction terms in a quadratic specification of $\overrightarrow{D}_o(x, y, b)$ are jointly equal to zero.

Therefore, we restrict the quadratic form to a linear one:

$$\overrightarrow{D}_o(x, y, b) = \sum_{n=1}^{N} \beta_n x_n + \sum_{g=1}^{G} \gamma_g y_g + \sum_{w=1}^{B} \phi_w b_w$$

$$+ \sum_{t=1}^{\tau} \gamma_t d_t + \sum_{i=1}^{F} \gamma_i d_i + \epsilon_{it}. \quad (3)$$
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where

\[ \epsilon_{it} = (v_{it} - u_{it}), \]  \hspace{1cm} (4)

where we specify that

1. \( \epsilon_{it} \) is an additive error
2. with a one-sided component, \( u_{it} \),
3. and a standard noise component, \( v_{it} \), with zero mean.

Further, \( d_t \) is a time dummy and \( d_i \) is a firm dummy.
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In the first stage, we compute the within IV estimator using time-demeaned data, which eliminates all time-invariant variables, such as those for sex, race, and mother’s background.
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All econometrics texts we are aware of are either silent on the ability to recover the effects of these variables or imply that this information is lost.

This need not be the case, as indicated in Hausman and Taylor (1981).

Using a second-stage regression, we recover consistent partial effects for the time-invariant variables.

We adjust the second-stage estimated standard errors, since they are based on first-stage estimated coefficients.

This approach has not been used before in the child health production literature.
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Consider a panel data set comprised of $F$ family units, $i = 1, \ldots, F$, over $T$ time periods, $t = 1, \ldots, T$. 
Further, let the \((N \times 1)\) vector of inputs be divided into a time-varying and a time-invariant component, where

1. \(x_{it} = (x_{1,it}, \ldots, x_{M,it})\) is a \((M \times 1)\) vector of time-varying inputs and

2. \(z_i = (z_{1i}, \ldots, z_{Ki})\) is a \((K \times 1)\) vector of time-invariant inputs. Also let

3. \(y_{it} = (y_{1,it}, \ldots, y_{G,it})\) be a \((G \times 1)\) vector of good time-varying outputs, and

4. \(b_{it} = (b_{1,it}, \ldots, b_{B,it})\) be a \((B \times 1)\) vector of time-varying bads.
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We write the directional distance function (without firm and time dummies) as

\[ 0 = \overrightarrow{D}_o(x_{it}, z_i, y_{it}, b_{it}; 0, 0, 1, -1) + \nu_{it} - u_{it}, \]

where the one-sided term, \( u_{it} \), measures the family-specific inefficiency.
Our linear specification for the directional distance function can be written as

\[ \overrightarrow{D}_o(x_{it}, z_i, y_{it}, b_{it}) = x_{it}\beta + z_i\theta + y_{it}\gamma + b_{it}\phi. \] (7)
These group-mean residuals from the first stage, $\hat{\theta}_i$, become the left-hand-side of the second-stage regression, which is

$$\hat{\theta}_i = z_i \delta + \xi_i,$$

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where the \( z_i \) are the time-invariant variables that were differenced out of the first-stage regression, and \( \xi_i \) is a random error term.
To estimate the technical inefficiency of each household, we obtain $\hat{\epsilon}_{it} = \hat{v}_{it} - \hat{u}_{it}$.

We then regress $-\hat{\epsilon}_{it} = \tilde{\epsilon}_{it} = \hat{u}_{it} - \hat{v}_{it}$ on a set of child dummies, and interactions of child dummies and time to separate the child-specific inefficiency from noise.

The fitted values, $\tilde{u}_{it}$, of this regression are consistent estimators of $\hat{u}_{it}$. 
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For each $i$, we adjust the value of $\tilde{u}_{it}$, $\tilde{u}_{it}^F$, so it is non-negative.

$\tilde{u}_{it}^F \geq 0$ is our measure of the technical inefficiency for each household.

To allow consistent comparisons among all output and input marginal effects, continuous input and output measures are standardized.

Marginal effects are in standard deviations.

We determine the effect of any variable on any other variable in the first stage, using the implicit function rule.
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In each of the 1994, 1996, 1998, and 2000 interview waves, all of our panel children received the Peabody Individual Achievement Tests in Mathematics (PIATMATH) and Reading Recognition (PIATREAD).

We estimated the largest possible balanced panel in order to facilitate the comparison of productivity measures over time. We find no evidence of sample selection bias.

Since we have exhausted our set of feasible instruments, we employ the bootstrap estimator to correct for the bias caused by weak instruments.
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Table 2: First Stage Estimation:  
Time-Demeaned Variables with Instruments

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (Asy. t-value)</th>
<th>No Bias Correction</th>
<th>Bias Correction</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Outputs:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PIAT_READ</td>
<td>-0.23365 (-2.17208)**</td>
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</tr>
<tr>
<td>PIAT_MATH</td>
<td>-0.45727 (-4.00839)**</td>
<td>-0.53395 (-6.01766)**</td>
<td></td>
</tr>
<tr>
<td>BPI</td>
<td>0.30908 (4.60839)**</td>
<td>0.30855 (10.75105)**</td>
<td></td>
</tr>
<tr>
<td><strong>Inputs:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CIGARETTES</td>
<td>-0.20168 (-1.73677)*</td>
<td>-0.31297 (-2.65002)**</td>
<td></td>
</tr>
<tr>
<td>INCOME/NUMCHILD</td>
<td>-0.00879 (-0.94141)</td>
<td>-0.00391 (-0.42215)</td>
<td></td>
</tr>
<tr>
<td>MOMWKHRS × AFQT</td>
<td>-0.19669 (-2.09073)**</td>
<td>-0.21786 (-16.94059)**</td>
<td></td>
</tr>
<tr>
<td>HEALTH</td>
<td>-0.00576 (-0.04421)</td>
<td>-0.03316 (-0.35674)</td>
<td></td>
</tr>
<tr>
<td>PUBSC</td>
<td>-0.01756 (-0.28071)</td>
<td>-0.14255 (-2.43192)**</td>
<td></td>
</tr>
<tr>
<td>PRIVSC</td>
<td>0.14519 (0.63301)</td>
<td>-0.09403 (-0.43048)</td>
<td></td>
</tr>
<tr>
<td>NBRATE_URBAN</td>
<td>-0.00480 (-0.3380)</td>
<td>0.01026 (4.72960)**</td>
<td></td>
</tr>
<tr>
<td>SUMSCHOOL</td>
<td>0.02141 (1.38062)</td>
<td>0.03325 (3.99114)**</td>
<td></td>
</tr>
<tr>
<td><strong>Time:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AGECH</td>
<td>0.50295 (5.21652)**</td>
<td>0.68336 (47.7120)**</td>
<td></td>
</tr>
<tr>
<td>AGECH2</td>
<td>-0.01328 (-3.92153)**</td>
<td>-0.02158 (-40.9928)**</td>
<td></td>
</tr>
</tbody>
</table>

Note: Asymptotic statistics in parentheses are computed using the corrected standard errors. A double (single) asterisk denotes significance at the .05 (.10) level of a two-tailed test.
Table 3: Second-Stage Estimation: Time-Invariant Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (Asy. t-value)</th>
<th>Bias Correction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Bias Correction</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Parent and Child Characteristics:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTERCEPT</td>
<td>-3.49650 (-5.50947)**</td>
<td>-4.41711 (-7.86987)**</td>
</tr>
<tr>
<td>BLACK</td>
<td>-0.11871 (-1.27360)</td>
<td>-0.15827 (-1.14142)</td>
</tr>
<tr>
<td>HISPANIC</td>
<td>-0.26586 (-3.00727)**</td>
<td>-0.38291 (-2.57812)**</td>
</tr>
<tr>
<td>BOY</td>
<td>0.19196 (3.34241)**</td>
<td>0.23684 (2.87352)**</td>
</tr>
<tr>
<td>HEAR_DIFF</td>
<td>0.06967 (0.44551)</td>
<td>0.07902 (0.40175)</td>
</tr>
<tr>
<td>LEARN_DIS</td>
<td>-0.80654 (-2.71830)**</td>
<td>-0.90956 (-2.08524)**</td>
</tr>
<tr>
<td>HOME02</td>
<td>0.24089 (6.82278)**</td>
<td>0.28965 (4.99066)**</td>
</tr>
<tr>
<td>EDUC_MOTH</td>
<td>0.01053 (0.28798)</td>
<td>0.01805 (0.35817)</td>
</tr>
<tr>
<td>EDUC_FATH</td>
<td>0.02352 (0.58438)</td>
<td>0.02533 (0.44715)</td>
</tr>
<tr>
<td>BIRTH_ORDER</td>
<td>0.01560 (0.59227)</td>
<td>0.01283 (0.31625)</td>
</tr>
<tr>
<td>BIRTH_WT</td>
<td>0.07506 (0.44466)</td>
<td>0.09641 (0.41918)</td>
</tr>
<tr>
<td>BIRTH_WT2</td>
<td>-0.13541 (-0.81155)</td>
<td>-0.18696 (-0.80859)</td>
</tr>
<tr>
<td>HS_1YR</td>
<td>-0.06775 (-0.68032)</td>
<td>-0.11624 (-0.88414)</td>
</tr>
</tbody>
</table>

Note: Asymptotic t-statistics in parentheses are computed using the corrected standard errors. A double (single) asterisk denotes significance at the .05 (.10) level of a two-tailed test.
Table 4: Average Child Technical Efficiencies

<table>
<thead>
<tr>
<th>Year</th>
<th>Technical Efficiency Score</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1994</td>
<td></td>
<td>0.7796</td>
<td>0.0736</td>
</tr>
<tr>
<td>1996</td>
<td></td>
<td>0.7816</td>
<td>0.0773</td>
</tr>
<tr>
<td>1998</td>
<td></td>
<td>0.7500</td>
<td>0.0829</td>
</tr>
<tr>
<td>2000</td>
<td></td>
<td>0.7203</td>
<td>0.0918</td>
</tr>
<tr>
<td>Child Age</td>
<td>PC</td>
<td>TC</td>
<td>EC</td>
</tr>
<tr>
<td>-----------</td>
<td>----------</td>
<td>----------</td>
<td>----------</td>
</tr>
<tr>
<td>5.</td>
<td>0.47351</td>
<td>0.46670</td>
<td>0.00681</td>
</tr>
<tr>
<td>6.</td>
<td>0.41878</td>
<td>0.42010</td>
<td>-0.00132</td>
</tr>
<tr>
<td>7.</td>
<td>0.37840</td>
<td>0.39246</td>
<td>-0.01406</td>
</tr>
<tr>
<td>8.</td>
<td>0.34710</td>
<td>0.37793</td>
<td>-0.03083</td>
</tr>
<tr>
<td>9.</td>
<td>0.31347</td>
<td>0.34468</td>
<td>-0.03120</td>
</tr>
<tr>
<td>10.</td>
<td>0.26579</td>
<td>0.29643</td>
<td>-0.03064</td>
</tr>
<tr>
<td>11.</td>
<td>0.22586</td>
<td>0.25965</td>
<td>-0.03379</td>
</tr>
<tr>
<td>Avg.</td>
<td>0.34613</td>
<td>0.36542</td>
<td>-0.01929</td>
</tr>
</tbody>
</table>
KEY RESULTS

▶ Many of the time-invariant variables (recovered from the second stage) are highly significant.

▶ Children’s cognitive/behavioral productivity growth is highest at their youngest age (5 years) and steadily diminishes thereafter.

▶ The major factor causing positive productivity growth to fall is declining technical change, rather than the observed negative efficiency change.

▶ The importance of child maturation is substantial:

1. A one percent increase in child age is nearly equal in importance to a one percent improvement in the child’s home environment and is more important than a one percent reduction in other inputs, such as mother’s cigarette consumption or effective home time.

2. Our result on the relative importance of child maturation is consistent with the fundamental principles of the child development literature.
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