The Effects of Children's Time Use and Home and Neighborhood Quality on their Body Weight and Cognitive/Behavioral Development

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Abstract

We estimate a directional distance function to assess the impacts of multiple time-varying parent and child inputs on a cluster of jointly produced child outcomes for children aged 7 to 13 years. The directional distance function specification avoids several well-known empirical problems associated with analysis of household production data, namely, the need to aggregate inputs and outputs, assume separability among inputs and outputs, or estimate reduced form equations. Using a balanced panel of families from the National Longitudinal Survey of Youth-Child Sample for 1996 to 2000, we assess the marginal contributions of home and neighborhood environmental quality and children's time allocations, on their math and reading performance, behavior problems, and body mass index. We also measure productivity growth, technical change, efficiency change, and technical efficiency for production of child outcomes. Our results indicate significant jointness among good and bad child outcomes. Significant improvements in children's good outcomes and reductions in bad outcomes are also associated with a better home and parent perceived neighborhood environment, Head Start participation, and increased family time spent together during meals. Children's productivity growth is found to be highest at age 8 years and diminishes thereafter.

1. Introduction

The prevalence of childhood overweight and obesity in the US and other developed countries is increasing (NCHS, 2001; Hedley et al., 2004). This trend is especially disturbing as overweight children are at significantly higher risk of being overweight as adults. The Centers for Disease Control and Prevention estimates that the number of obese US adults has steadily increased from 19.4 percent in 1997 to 26.6 percent in 2007 (Flegal, 2010); while over this same time period, the number of obese US children aged 6-11 years increased from 4 to 18.8 percent. Adding to this group the number of US children aged 6-11 who are "at risk of obesity," the combined 2007 number of overweight or obese children is 31 percent (Sen et al., 2009). While obesity is clearly linked to numerous adverse health effects in adults, effects seen in obese children are similar to those seen in obese adults, including high cholesterol, hypertension, type 2 diabetes, and sleep apnea (NIH, 2000; Kumanyika, 2001). As would be expected among children who are still developing, obesity can reduce children's mental and social well-being. Numerous studies have linked childhood obesity to lower academic performance (Sabia, 2007; Cawley and Spiess, 2008), as well as various social and behavioral problems including aggressiveness (Lumeng et al., 2003; Gortmaker et al., 1990) and social isolation (Pine et al., 2001).

While the most common cause of obesity in children and adults is a net energy imbalance over time (calories consumed exceed calories used), this imbalance is believed to result from influences and interactions of a number of factors (Classen and Hokayem, 2005). Interactions among these factors–rather than any single factor–are thought to cause childhood obesity (WHO, 2000; Jordan and Robinson, 2008). One principal factor is genes. In some cases, parent obesity is a stronger predictor of childhood obesity than the child's weight status alone (Biron et al., 1977; AAP, 2003). However, there is emerging consensus that home and neighborhood environments play a key role in a child's excessive weight gain (Burdette et al., 2006; Diez-Roux, 2001). Numerous studies indicate a strong positive association between physically active lifestyles and children's healthy physical development (USDHHS, 2000). However, the CDC reports that numbers of US children who do not participate in organized school or nonschool activities is on the rise; roughly 36 percent of school-aged children meet the current recommended levels of physical activity (USDHHS, 2008). Studies examining the links between childhood obesity and socioeconomic, demographic, and home and neighborhood environments suggest that reduction of obesity among US children requires efforts from both caregivers and policymakers to foster environments supportive of children's healthy lifestyles, such as better structuring children's time use (Sener et al., 2008), reducing neighborhood crime (Mujahid et al., 2008) and fast food availability (Chou et al., 2008), and increasing accessibility to playgrounds and recreation facilities (Humpel et al., 2002).

The household production literature, both empirical (Aiken, 2006) and theoretical (Pollak and Wachter, 1975), recognizes the household as a multiple-output producer. However, only a handful of studies to date have analyzed empirically the family's production of multiple, often interrelated outputs. Data and estimation issues generally complicate these efforts. Current approaches in economics to assess parental inputs on children's developmental outcomes include (i) collapsing multiple outcomes into single scalar dependent variable measures, such as health status, cognitive ability, or growth (e.g., Cunha and Heckman, 2008); (ii) treating multiple outcomes as separable to facilitate independent, single-equation regressions for each outcome of interest (Blau, 1999); or (iii) estimating reduced-form specifications (Taylor et al., 2004) to avoid modeling input and output endogeneity directly. The problem with these approaches is that they cannot accommodate and/or assess the degree of jontness in production likely occurring when households combine multiple good or bad inputs to produce multiple good or bad child outcomes.

This study uses a directional distance function to specify a household's production technology. The directional distance function is useful because it readily handles the case of joint production of multiple outputs (good and bad) when data on only input and output quantities are available. We use a fixed-effects estimator with instrumental variables to compute our multiple-input, multiple-output directional distance function using a 4-year balanced panel of families from the National Longitudinal Survey of Youth (NLSY), and the NLSY Child Sample. The estimated directional distance function then allows us to assess the marginal impacts of parent and child inputs (e.g., home and neighborhood environmental quality, and child's time use) on a cluster of plausibly interrelated good and bad child outcomes (e.g., child obesity and cognitive performance). Also assessable is the degree of jointness between these outcomes (e.g., the impact of child obesity on cognitive performance). The onerous task of correctly specifying a system of simultaneous equations with no a priori cross-equation restrictions to assess jointness between multiple dependent variables is avoided, as is estimation of reduced form equations, the latter of which precludes estimation of marginal impacts of endogenous inputs upon endogenous child outcomes.

The child development literature emphasizes that development is a time-varying process involving brain and nervous system maturation and learning in combination with family and environmental inputs (Cunha and Heckman, 2007; Ruffin, 2001). Estimation of a directional distance function makes possible the analysis of the effect of aging (child maturation) on sample children's outcome production possibilities for a given quantity of inputs. Since households' production technologies for child outcomes likely change as children age, our results can be used to assess the degree of technical change (TC) among households' in their production of these outcomes. For example, a positive TC indicates that sample households' "best practice" frontier has shifted outward over time. Also determinable is a measure of efficiency change (EC), indicating the extent to which children in non-frontier households are "catching up" to frontier children over time. The sum of TC and EC provides a measure of overall productivity change (PC), the growth in productivity of child inputs over time. Currently, very few empirical studies of the household and child development assess any of these age-related changes production technology. None exploit the aforementioned analytical and empirical advantages of the directional distance function framework.[1]

Our results reveal several important interactions among good and bad child inputs and outcomes. First, for children with below sample average scores in reading and math performance, math and reading performance scores are substitutes. But for sample children who score average or above in math and in reading, they are complements. Also evident among our sample children is a significant negative association between excessive weight gain and lower reading and math performance scores. Among all sample children we find that a better home and (parent perceived) neighborhood environment, as well as increased time spent together during meals, improve children's good outcomes (reading and math performance) and reduce bad outcomes (behavior problems and overweight). Children's cognitive/behavioral productivity growth is found to increase from sample ages 7 to 8, but diminish thereafter, suggesting that home and neighborhood contributions to child

[1] While Todd and Wolpin (2007) and Blau (1999) include time dummies in their single-equation, least squares child human capital production functions, they do not report the effects of child maturation on the production process. Cunha and Heckman (2008) and Cunha et al. (2010) apply latent variable methods to multistage production functions to assess the effects of child maturation and parental investments and attributes upon children's cognitive and noncognitive skill formation.

outcomes diminish as children approach adolescence. The choice of alternative direction vectors used to compute distances to the stochastic frontier does little to alter our results.

We organize the remainder of the paper as follows. The next section discusses properties of the directional distance function and the calculation of productivity change. Section 3 reports empirical results, and Section 4 concludes.

2. The Directional Distance Function

Let there exist within each household a production technology for children's human capital outcomes. Parents combine multiple inputs, either N good inputs, $\mathbf{x} = (x_1, \ldots, x_N) \in R_+^N$, or J bad inputs, $\tilde{\mathbf{x}} = (\tilde{x}_1, \ldots, \tilde{x}_J) \in R_+^J$, to produce multiple child outcomes, which classify as M good outcomes, $\mathbf{y} = (y_1, \ldots, y_M) \in R_+^M$., and L bad outcomes, $\tilde{\mathbf{y}} = (\tilde{y}_1, \ldots, \tilde{y}_L) \in R_+^L$, produced jointly with $\mathbf{y}$. Following Chambers et al. (1998) and Färe et al. (2005), we define the household's output directional distance function as

$$\vec{D}_o(\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y}, \tilde{\mathbf{y}}; \mathbf{0}, \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) = \sup\{\beta : (\mathbf{y} + \beta\mathbf{g}_y, \tilde{y} - \beta\mathbf{g}_{\tilde{y}}) \in P(\mathbf{x}, \tilde{\mathbf{x}})\}, \tag{2.1}$$

where $P(\mathbf{x}, \tilde{\mathbf{x}})$ is the set of good and bad outcomes that can be produced with $(\mathbf{x}, \tilde{\mathbf{x}})$, and direction $(\mathbf{0}, \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}})$, such that $(\mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) \neq (\mathbf{0}, \mathbf{0})$. The output directional distance function measures the increase (decrease) in good outcomes (bad outcomes) in the direction $\mathbf{g}_y$ $(-\mathbf{g}_{\tilde{y}})$ for a given level of observed inputs in order to move towards the "best practice" frontier, P. Outcome shortfalls relative to the best practice frontier are measures of technical inefficiency in the household's production of child human capital outcomes. This measure is zero when the household is on P and is greater than zero when the household lies below P.

Necessary properties of the output directional distance function include:

$$\overrightarrow{D}_o(\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y} + \alpha\mathbf{g}_y, \tilde{y} - \alpha\mathbf{g}_{\tilde{\mathbf{y}}}; \mathbf{0}, \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) \geq 0 \iff (\mathbf{y}, \tilde{\mathbf{y}}) \in P(\mathbf{x}, \tilde{\mathbf{x}}), \tag{2.2}$$

$$\overrightarrow{D}_o(\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y} + \alpha\mathbf{g}_y, \tilde{y} - \alpha\mathbf{g}_{\tilde{\mathbf{y}}}; \mathbf{0}, \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) = \overrightarrow{D}_o(\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y}, \tilde{\mathbf{y}}; \mathbf{0}, \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) - \alpha, \tag{2.3}$$

$$(\mathbf{y}', \tilde{\mathbf{y}}) \leq (\mathbf{y}, \tilde{\mathbf{y}}) \in P(\mathbf{x}, \tilde{\mathbf{x}}) \rightarrow \overrightarrow{D}_o(\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y}', \tilde{\mathbf{y}}; \mathbf{0}, \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) \geq \overrightarrow{D}_o(\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y}, \tilde{\mathbf{y}}; \mathbf{0}, \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}), \tag{2.4}$$

$$(\mathbf{y}, \tilde{\mathbf{y}}') \geq (\mathbf{y}, \tilde{\mathbf{y}}) \in P(\mathbf{x}, \tilde{\mathbf{x}}) \rightarrow \overrightarrow{D}_o(\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y}, \tilde{\mathbf{y}}'; \mathbf{0}, \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) \geq \overrightarrow{D}_o(\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y}, \tilde{\mathbf{y}}; \mathbf{0}, \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}). \tag{2.5}$$

Equation (2.2) states that the outcome directional distance function will be non-negative for all feasible outcome vectors. Equation (2.3) is the translation property for the directional vector, which is analogous to the property of linear homogeneity with a standard output distance function.[2] Next, equation (2.4) tells us that if good outcomes increase for a given level of bad outcomes and inputs, then the household's technical inefficiency will decrease. Last, equation (2.5) says that if bad outputs increase for a given level of inputs and good outputs, then the household's technical efficiency decreases.

Estimation Strategy. To implement the above model, we employ a balanced panel of F children, $i = 1, \ldots, F$, spanning T time periods, $t = 1 \ldots, T$. Hereafter we define each variable within $\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y}$, and $\tilde{\mathbf{y}}$ as (FT $\times$ 1) vectors. Since many of the inputs we employ in our directional distance function are measured as zero-bounded or binary, our distance function is specified as quadratic. In preliminary estimates, we failed to reject the null hypothesis that the squared and interaction terms involving all inputs (with the exception of child age) are jointly equal to zero. In addition, we failed to reject the null hypothesis

[2] If $g_y = 1$ and $g_{\tilde{y}} = -1$, the translation property implies that if a good outcome increases by $\alpha\mathbf{g}_y$ while a bad outcome falls by $\alpha\mathbf{g}_b$, then the distance function declines by α, i.e., a household's child human capital production will be more efficient by the amount α.

that time is separable from all inputs and outputs. As a result, we estimate the following modified quadratic specification, which still allows for interactions among all outputs:

$$\begin{aligned}
\overrightarrow{D}_{o,it}(\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y}, \tilde{y}) = & \sum_{n=1}^{N} \gamma_n x_{it,n} + \sum_{j=1}^{J} \gamma_j \tilde{x}_{it,j} + \sum_{m=1}^{M} \gamma_m y_{it,m} + \sum_{l=1}^{L} \gamma_l \tilde{y}_{it,l} \\
& + \frac{1}{2} \sum_{m=1}^{M} \sum_{m'=1}^{M} \gamma_{mm'} y_{it,m} y_{it,m'} + \frac{1}{2} \sum_{l=1}^{L} \sum_{l'=1}^{L} \gamma_{ll'} \tilde{y}_{it,l} \tilde{y}_{it,l'} \\
& + \sum_{l=1}^{L} \sum_{m=1}^{M} \gamma_{lm} \tilde{y}_{it,l} y_{it,m} + \gamma_{t1} t + \gamma_{t2} t^2 + \varepsilon_{it},
\end{aligned} \tag{2.6}$$

such that

$$\varepsilon_{it} = \nu_{it} - \mu_{it}, \tag{2.7}$$

where ε_t is an additive error term with a one-sided component, $\mu_{it} > 0$ (which captures technical inefficiency), and a standard two-sided noise component, ν_{it}, with zero mean. The left-hand side of (2.6) is set to zero for all observations. To satisfy the translation property in equation (2.3), the following restrictions are imposed:

$$\begin{aligned}
\sum_{m=1}^{M} \gamma_m g_m - \sum_{l=1}^{L} \gamma_l g_l &= -1, \\
\sum_{m=1}^{M} \gamma_{mm'} g_m - \sum_{l=1}^{L} \gamma_{m'l} g_l &= 0, \forall\, m', \\
\sum_{l=1}^{L} \gamma_{ll'} g_l - \sum_{m=1}^{M} \gamma_{ml'} g_m &= 0, \forall\, l'.
\end{aligned} \tag{2.8}$$

We also impose symmetry upon the doubly-subscripted coefficients in (2.6), and we satisfy equation (2.2) after estimation using a normalization as discussed below. Since the left-hand-side of (2.6) is zero for all observations, marginal impacts of individual model variables along the frontier upon other model variables are assessed by means of the implicit function rule. For example, the impact of a bad outcome upon a good outcome is

$-(\partial \overrightarrow{D}_o/\partial \tilde{y}_l)/(\partial \overrightarrow{D}_o/\partial y_m), \forall\ m, l$, and the impact of a good input upon a good outcome is $-(\partial \overrightarrow{D}_o/\partial x_n)/(\partial \overrightarrow{D}_o/\partial y_m), \forall\ n, m$.

With panel data, we could estimate equation (2.6) treating the μ_{it} as either fixed or random. But since a random-effects approach imposes the generally implausible assumption that the μ_{it} are uncorrelated with included variables, we use a fixed-effects approach. The fixed-effects approach eliminates all time-invariant unobservables so that our estimators are consistent even though we allow for non-zero correlation between the unobservables and the included variables. Thus, we include N child-specific dummy variables, d_i, in (2.6) before estimation to eliminate unobserved, time-invariant heterogeneity. Because of the large number of children in our sample, we actually estimate (2.6) using time-demeaned data without the d_i, but the exposition which follows is clearer and less notation-burdened if we employ the dummy-variable notation. Because we distinguish our observations by child age, the estimated coefficients with the two methods are equivalent. We adjust the estimated standard errors obtained using time-demeaned data for lost degrees of freedom.

Estimating PC and TE. Estimates of household-specific PC, TC, and EC (as well as TE) derive from equation (2.6) as follows. The fitted directional distance function equals the negative of the fitted composite error term, $\hat{\varepsilon}_{it}$, which represents unobserved household inefficiency at producing child outcomes. By computing the within estimator for (2.6) using time-demeaned data, we have effectively subtracted $\vartheta_i d_i$ from the composite error term (where d_i is a child-specific dummy) and added this term to the estimated regression model. That is, computing the within estimator is equivalent to having estimated the following model:

$$0 = \overrightarrow{D}_o(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}\mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) + \vartheta_i d_i + \varepsilon^*_{it}, \tag{2.9}$$

where $\vartheta_i d_i$ has been subtracted from the composite error term, ε_{it}, in (2.6), which is now equal to $\varepsilon^*_{it} = \nu_{it} - \mu_{it} - \vartheta_i d_i$.

Since our goal is to measure PC, TC, and EC in terms of percentage changes, we transform the directional distance function measures into corresponding Malmquist distance function measures. Adding the superscript, t, to indicate the time period, and, following Balk et al. (2008), the following Malmquist output-oriented distance function measures are obtained:

$$
\begin{aligned}
&D_o^{t+1}(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) = 1/(1 + \overrightarrow{D}_o^{t+1}(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}))\\
&D_o^{t+1}(\mathbf{x}_{i,t+1}, \tilde{\mathbf{x}}_{i,t+1}, \mathbf{y}_{i,t+1}, \tilde{\mathbf{y}}_{i,t+1}) = 1/(1 + \overrightarrow{D}_o^{t+1}(\mathbf{x}_{i,t+1}, \tilde{\mathbf{x}}_{i,t+1}, \mathbf{y}_{i,t+1}, \tilde{\mathbf{y}}_{i,t+1}))\\
&D_o^{t}(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) = 1/(1 + \overrightarrow{D}_o^{t}(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}))\\
&D_o^{t}(\mathbf{x}_{i,t+1}, \tilde{\mathbf{x}}_{i,t+1}, \mathbf{y}_{i,t+1}, \tilde{\mathbf{y}}_{i,t+1}) = 1/(1 + \overrightarrow{D}_o^{t}(\mathbf{x}_{i,t+1}, \tilde{\mathbf{x}}_{i,t+1}, \mathbf{y}_{i,t+1}, \tilde{\mathbf{y}}_{i,t+1})).
\end{aligned} \tag{2.10}
$$

Here we assume that $\hat{u}_{it}$ and $\hat{v}_{it}$ are respectively one- and two-sided error terms for the distance function

$$1 = D_o^t(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) \exp(\epsilon_{it}), \tag{2.11}$$

where $\epsilon_{it} = v_{it} - u_{it}$. After adding a child dummy effect, $\zeta_i d_i$, for child i to the estimated distance function and subtracting this term from ϵ_{it}, we obtain

$$1 = D_o^t(\mathbf{x}_{it}, \tilde{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) \exp(\zeta_i d_i) \exp(\epsilon^*{}_{it}), \tag{2.12}$$

where

$$\epsilon^*_{it} = v_{it} - u_{it} - \zeta_i d_i. \tag{2.13}$$

Using fitted values and taking logs of (2.12), we obtain

$$0 = \ln \hat{D}_o^t(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) + \hat{\zeta}_i d_i + \hat{\epsilon}^*_{it}. \tag{2.14}$$

Combining (2.13) in terms of fitted values with (2.14), we obtain

$$\hat{u}_{it} - \hat{v}_{it} = \ln \hat{D}_o^t(\mathbf{x}_{it}, \tilde{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}). \tag{2.15}$$

We compute the fitted directional distance with $\vartheta_i = 0$ in (2.9) and use (2.10) to transform this directional distance measure into its corresponding Malmquist distance measure. We then use (2.15) to obtain $\hat{u}_{it} - \hat{v}_{it}$. To remove the noise term, $\hat{v}_{it}$, we regress $\tilde{\epsilon}_{it} = -\hat{\epsilon}_{it} = \hat{u}_{it} - \hat{v}_{it}$ on a set of child dummies and the interactions of child dummies with time using

$$\tilde{\epsilon}_{it} = \delta_0 + \delta_i d_i + \sum_t \delta_{it} d_i t + \varphi_{it}, \tag{2.16}$$

where φ_{it} is a random error term uncorrelated with the regressors. The fitted values, $\tilde{u}_{it}$, of this regression are consistent estimators of $\hat{u}_{it}$.

Since we did not impose the restriction that $\tilde{u}_{it} > 0$ during estimation, we now do so by adding and subtracting $\tilde{u}_t = \min_i(\tilde{u}_{it})$ from our fitted version of $\ln \hat{D}_o^t(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) + \hat{v}_{it} - \tilde{u}_{it}$. This yields

$$\begin{aligned} 0 &= \ln \hat{D}_o^t(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) + \hat{v}_{it} - \tilde{u}_{it} + \tilde{u}_t - \tilde{u}_t, \\ &= \ln \hat{D}_o^t(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) - \tilde{u}_t + \hat{v}_{it} - \tilde{u}_{it}^{\mathcal{F}}, \\ &= \ln \hat{D}_o^{\mathcal{F},t}(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) + \hat{v}_{it} - \tilde{u}_{it}^{\mathcal{F}}, \end{aligned} \tag{2.17}$$

where the log of the fitted frontier shadow distance function in period t, $\ln \hat{D}_o^{\mathcal{F},t}(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it})$, is defined as $\ln \hat{D}_o^t(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) - \tilde{u}_t$, and $\tilde{u}_{it}^{\mathcal{F}} = \tilde{u}_{it} - \tilde{u}_t \geq 0$. Thus we estimate household technical efficiency, TE_{it}, as

$$\mathrm{TE}_{it} = \exp(-\tilde{u}_{it}^{\mathcal{F}}). \tag{2.18}$$

Estimation of EC_{it} follows as

$$\mathrm{EC}_{it} = \Delta\mathrm{TE}_{it} = \mathrm{TE}_{f,t+1} - \mathrm{TE}_{it}. \tag{2.19}$$

After eliminating our residuals $\hat{v}_{it}$ and $\tilde{u}_{it}^{\mathcal{F}}$, TC_{it} is estimated as the difference between $\ln \hat{D}_o^{\mathcal{F},t+1}(\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y}, \tilde{\mathbf{y}})$ and $\ln \hat{D}_o^{\mathcal{F},t}(\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y}, \tilde{\mathbf{y}})$, holding all household input and child outcome quantities constant:

$$\begin{aligned}\mathrm{TC}_{it} &= \ln \hat{D}_o^{t+1}(\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y}, \tilde{\mathbf{y}}) - \tilde{u}_{t+1} - [\ln \hat{D}_o^{t}(\mathbf{x}, \tilde{\mathbf{x}}, \mathbf{y}, \tilde{\mathbf{y}}) - \tilde{u}_t] \\ &= \hat{\gamma}_{t1} + \hat{\gamma}_{t2}[(t+1)^2 - t^2] - (\tilde{u}_{t+1} - \tilde{u}_t). \end{aligned} \tag{2.20}$$

In equation (2.20), the time change in the frontier intercept, $\tilde{u}_t$, impacts TC_{it} as well as EC_{it}. Finally, PC_{it} calculates as the sum:

$$\mathrm{PC}_{it} = \mathrm{EC}_{it} + \mathrm{TC}_{it}. \tag{2.21}$$

We interpret TC as the outward shift in households' production possibilities over time, and EC as the rate of catching up to the frontier over time by non-frontier households.

The Importance of Standardized Units. Since we estimate a directional distance function, all point-to-point distances from inside the frontier to the frontier are unit sensitive (i.e., all changes in one outcome or input relative to another must be unit free). If units of all variables are not standardized, then a given absolute increase in one variable is not comparable to the same increase in another variable, holding all other variables constant. To allow consistent comparisons among all outcome and input marginal effects, all continuous input and outcome measures in our empirical model are standardized to a zero mean and unit variance. All dichotomous variables are left unchanged. Thus, for example, the marginal impact of an input on any outcome is in standard deviations. Moreover, if a given family has a $\tilde{u}_{it}^{\mathcal{F}}$ (technical inefficiency measure) equal to 1.0, its child could have good (bad) outcome values one standard deviation higher (lower) using the same quantity of observed inputs if this family operated on the "best practice" frontier.

3. Data, Estimator, and Empirical Results

Data. Our data comes from the National Longitudinal Survey of Youth (NLSY79), the NLSY79 Geocode files (NLSY-G), and the NLSY79 Child Sample (NLSY79-CS). The Surveys provide a nationally representative longitudinal sample with a wide variety of information on parents and children along with information on parental input use and a variety of child outcomes (Bureau of Labor Statistics 2003). NLSY79 is a nationally representative sample of individuals who were age 14-21 as of January 1, 1979, with significant oversamples of Blacks, Hispanics, and lower income Whites. The NLSY-G contains confidential state, county, and metropolitan statistical area information on NLSY79 respondents' current and historical residences, along with selected time-specific county and metropolitan area environmental data. NLSY79-CS is a sample of all children ever born to the women of the NLSY79. These surveys collect extensive information about schooling, employment, marriage, fertility, income, and participation in public programs, as well as other relevant topics such as detailed assessments of children's cognitive abilities, social and behavioral attributes, and qualities of each child's home environment. Interviews for NLSY79-CS have been conducted biannually since 1986.

Our analysis focuses on a balanced panel of NLSY79-CS children who were ages 81 to 119 months in 1996, 105 to 143 months in 1998, and 129 to 167 months in 2000. In each of the biannual interview waves, all of our 253 panel children received the Peabody Individual Achievement Tests in mathematics (PIATMATH) and reading recognition (PIATREAD). These tests, which have been widely used and accepted as valid instruments to measure children's ability in mathematics, oral reading, and the ability to derive meaning from printed words, serve as our outcome measures of child cognitive achievements. The tests are identical whatever the child's age, beginning with basic reading or mathematics skills questions, which then progressively increase in difficulty from preschool to high school levels. Thus a five-year-old is not expected to progress as far on either test as would a ten-year-old. As in Todd and Wolpin (2007), we use the raw individual test scores rather than percentile scores in order to capture any changes in normal absolute achievement over time due to changes in a child's receptivity and impacts of endogenous home and child inputs. Our interest focuses exclusively on 1996-2000 NLSY79-CS children in the seven to thirteen year-old age range for a couple of reasons. First, a large portion of a child's basic reading and arithmetic skills develop over this range. Second, a child's out-of-school time use becomes increasingly more "discretionary" after age seven.

Table 1 presents sample means and standard deviations for all variables employed in our empirical model. Our sample consists of 759 observations on the 253 households having no missing data for the years 1996, 1998, and 2000. For two reasons this sample is considerably smaller than used by previous studies (e.g., Blau 1999; Todd and Wolpin 2007) employing the NLSY79-CS. First, these studies estimated a series of single-equation, separable production functions so that deletion of missing observations on outcomes (or inputs) not being considered was unnecessary. Second, they combined data for all available years, resulting in a large, albeit highly unbalanced, panel. Here, use of a balanced panel enables us to consistently estimate children's productivity growth, with no missing estimates over any time periods, for the entire sample of children who mature together from age 7 to 13 years. While use of an unbalanced panel increases sample size, it also yields unequal numbers of child productivity growth measures observed over disparate time periods (i.e., missing estimates exist for some children). Unless annual changes in child productivity growth are collectively zero or are strictly linear, resulting PC, TC, and EC estimates will be biased. As evidenced in Table 2, estimated coefficients for child age and its square are highly significant, indicating that child productivity growth with advancing age is nonlinear. And while our balanced panel is considerably smaller than its unbalanced counterpart, we do not consider selection bias to be a problem since there is no evidence of systematic exclusion based on endogenous variables. In fact, the means of Table 1 variables for our selected sample are very close to those of the entire set of sampled households.

Parents and children together utilize many good and bad inputs to produce a broad range of good and bad child outcomes. However, data limitations preclude estimation of an all-encompassing multiple-input, multiple-output directional distance function. We narrow the scope of our analysis to a cluster of four child outcomes posited in the child health literature to be interrelated. We examine two time-varying good child outcomes (PIAT-MATH and PIATREAD), and two time-varying bad outcomes (BPI and BMI_HIGH). The behavioral problems index (BPI) assesses wide-ranging social and behavioral problems in children and is calculated from a series of questions on the frequency, range, and type of such problems as reported by the child's mother (Peterson and Zill, 1986). The index increases as these problems increase. The variable BMI_HIGH measures the amount by which each child's body mass index (BMI) exceeds his/her age- and gender-specific cut-off defined by the US Centers for Disease Control as "overweight." Unlike adults, no specific BMI cut-off applies to all children. Instead, age- and gender-specific growth charts based on national data from 1963-1994 (CDC, 2000) must be used to calculate the appropriate cut-offs for each sample child based upon gender and age. Children who are at or above the 85th percentile of the gender-specific BMI for their age group are considered overweight.

BMI_HIGH is either positive or zero. Thus for example, if child i has a BMI = 20 and his CDC age-specific maximum healthy BMI = 17, then i is overweight with a BMI_HIGH = 3. Conversely, if child j is the same age and gender as i and has a BMI = 17 or less, then j's BMI_HIGH = 0. The positive magnitude of each child's BMI net of his/her BMI cut-off measures each child's (potential) bad associated with his/her overweight.[3]

Endogenous parental inputs include the product of maternal work hours (MOMWKHRS) and her performance on the Air Force Qualifying Test (AFQT), whether the child participated at least 1 year in a Head Start program (HS1YR), the number of daily hours the family spends eating meals together, and the mother's perspective on the quality (5 = best,...,1 = worst) of their current neighborhood as a place for raising children (NBRATE) conditioned on whether the neighborhood is in an urban area (URBAN). As in Graham and Green (1984), the product of MOMWKHRS and AFQT reflects the mother's "effective time" (i.e., work time weighted by human capital) that she spends away from the subject child. Recent research has found that increased in maternal employment hours are associated with an increased risk of a child being overweight (e.g., Cawley and Liu, 2007), as well as reduced academic performance (Brooks-Gunn et al., 2002; Bernal, 2008). Head Start participation (HS1YR) and neighborhood quality (NBRATE) speak to the effects of extra-home learning and socialization activities and ease of access to these settings.[4]

The last parental input we include is a predetermined, time-invariant measure of each child's quality of home environment as assessed by the Home Observation Measurement of the Environment Short-Form, or HOME (Bradley and Caldwell, 1980). The HOME index

[3] An exceptionally low BMI also poses potential health risks (i.e., a bad outcome of being below his/her healthy weight range). However, none of our sample children had a BMI below their respective cut-offs that classify them as underweight.

[4] The neighborhood boundary to which NBRATE refers is defined by the child's mother. Neighborhood definitions used in most empirical studies of neighborhood effects on child development (e.g., Sanbonmatsu et al., 2006) are census tracts considerably larger than the boundaries for the physically close neighbors, institutions, and material features which matter most for child outcomes (Goux and Maurin, 2007).

consists of four evaluative questionnaires that differ by child age: ages 0-2, 3-5, 6-9, and 10-14 years. Questionnaire responses are used to compile a raw index score of the overall quality of the child's home environment, mother's emotional and verbal responsiveness, acceptance of, and involvement with her child, the safety and orderliness of the household, and presence of child activity variety, and learning materials. The age-specific raw scores are simple nonweighted sums of all individual questionnaire items (each item receives a 0 or 1 score). Because the content of each questionnaire (along with the potential raw score) changes as children age, a contemporaneous child HOME index measure is not constructible. In our empirical model, our variable HOME is the arithmetic mean of each child's raw HOME index scores compiled from the age 0-2 and 3-5 questionnaires. We interpret HOME as a predetermined, baseline measure of each child's home environmental quality input. HOME accounts for encouragement of the child's cognitive and social stimulation within the household; NBRATE accounts for it outside the household. These two socialization settings are complements (substitutes) if parents have more (less) incentive to enhance the home environment the more widely their values are held by their neighbors (Agee and Crocker, 2002; Bisin and Veralier, 2001).

It is not uncommon to find explanatory variables of interest in panel data sets that are time-invariant (such as HOME); however, in a fixed effects model these variables are generally considered "swept away" by the within estimator of the coefficients on the time-varying covariates. Nevertheless, it is possible to identify and consistently estimate marginal effects of time-invariant variables upon other variables in the model (both time-varying and time-invariant) by means of a two-stage procedure. We use this two-stage procedure to obtain consistent coefficient estimates for HOME (along with corrected standard errors), that are displayed in Table 2. While not discussed here, the details of this procedure are outlined in Agee, Atkinson, and Crocker (2008) along with an empirical illustration using a multiple-output directional distance function.

Endogenous child inputs include his/her daily hours (outside school) spent on homework (HRS/D_HMWK), reading for pleasure (HRS/_READ), and total weekly hours spent watching television (HRS/W_TV). The dummy variable, OUTSCH_REC, indicates whether the child confirms visitation to a recreation center or facility as a "regular activity" when not in school. Last, the dummy variable, HEALTH_MOBILITY, indicates whether the child has a preexisting health condition that limits physical mobility in any way.

Child age (AGECH), and age squared (AGECH2) enter our directional distance function to measure changes, via maturation, of the child's propensity to produce cognitive and noncognitive outcomes. Based on the child development literature, the age of the child, rather than the calendar year when the child ages, is critical for development and productivity change, assuming that the technology of the learning environment is relatively constant. Since this is clearly the case for the time span of our sample, and since the age of the child and calendar time are nearly collinear, we omit calendar time and specify child age as our measure of t.

Our list of instruments include all aforementioned exogenous and predetermined variables plus the mother's age (MOMAGE), education (MOMED), race (BLACK, HISPANIC), and hourly wage if employed (MOMWAGE). Family instruments include whether the father lives at home with the mother and subject child (DADPRSNT), family income (INCOME), family size (NUMCHILD), and religion (CATHOLIC). These variables correlate highly with the mother's choice of work hours, her neighborhood quality assessment, and frequency of family meals eaten together. Additional child-specific instruments include each child's baseline scores (the child's initial performances taken at age 2-4 years) on the Peabody Picture Vocabulary Test-Revised (PPVT-R), Motor and Social Development Scale (MSD), and Temperament Scale (TMP). Also included is the frequency of teacher assigned homework (HMWK_FREQ), the child's birth weight (BIRTHWT), gender (BOY), and height in inches (HEIGHT). A priori, these variables are clearly exogenous (by definition) or predetermined, and should correlate highly with our child outcome measures. Finally, we supplement the above list with residence-specific information that correlates strongly with the family's neighborhood environment. These include the crime rate (CRIME), unemployment rate (UNEMPL), and per capita number of physicians (PHYSICIANS), and female heads of household (FHEAD) in each family's county of residence. Other residence-specific variables admitted to our instrument set include the county price of cigarettes (PRICECIGS), and the state average pupil teacher ratio (PTRATIO) and teacher's salary (TSALARY). While these latter instruments seem ad hoc, our final choice of instruments was the set that passed the J-test for overidentification described below. To create an instrument set that is fully time-varying, following Wooldridge (2002) and others, we interact the set of time-invariant instruments with the set of time-varying instruments.

Hansen's (1982) J-test produces a test statistic of 18.68 with a probability value of .466, clearly failing to reject the null hypothesis of zero correlation of our over-identifying instruments with the error term. But while the simple correlations between our endogenous variables and instruments are strong, regressions of each time-demeaned endogenous variable on the full instrument set produced F statistics below 10 for two of the endogenous variables, MOMWKHRS∗AFQT, and HRS/D_READ∗AGECH. Further comparison of the instrumented versus non-instrumented within estimates suggested presence of weak instruments (see e.g., Cameron and Trivedi 2005).[5] Having exhausted our set of feasible instruments, we employed the bootstrap instrumental variables (BIV) estimator to correct for potential bias caused by weak instruments.

We employed 399 bootstrap replications. Formulas for the bootstrap bias correction are given in Shao and Tu (1995). Letting $\hat{\beta}$ denote the estimator of β for the within model, and defining each of B total bootstrap estimates as β_b^*, $b = 1 \ldots, B$, and their average as $\bar{\beta}^* = (1/B)\sum_{b=1}^{B} \beta_b^*$, the bootstrap bias estimator is

$$\text{BIAS}_{\text{Boot}} = (\bar{\beta}^* - \hat{\beta}), \tag{3.1}$$

and the bootstrap bias-adjusted (BA) estimator of β is

$$\hat{\beta}_{BA} = 2\hat{\beta} - \bar{\beta}^*. \tag{3.2}$$

The intuition of the BIV estimator is the following. We would like to compute the bias of $\hat{\beta}$ relative to β, but we do not know β. We thus treat $\hat{\beta}$ as the "true" value and determine the bias of the bootstrap estimator relative to this value. We then adjust $\hat{\beta}$ by this computed bias, assuming that the bias of the bootstrap estimator relative to $\hat{\beta}$ is the same as the bias of $\hat{\beta}$ relative to β.

Empirical Results. Estimates of our output directional distance function are reported in Table 2. Results are B2SLS bias corrected with bootstrap estimated standard errors. Standard errors are adjusted upwards to account for lost degrees of freedom due to time-demeaning of our data.

Table 2 estimates are based upon three alternative units of translation between the good and bad outcomes (i.e., direction vectors). The directional distance function estimates in column two of Table 2 assume the output direction vector of (1,-1), implying that, for

[5] The non-instrumented within estimates are available from the authors upon request.

a given level of inputs, this distance function requires increases (decreases) in good (bad) outcomes of the unit quantities 1 (-1), in standard deviation terms, in order to move closer to the best practice frontier. In preliminary regressions not reported, we estimated numerous directional distance functions specified with alternative direction vectors. We found that choice of any direction vector within the bounds of (2, -1) and (1, -2), as reported in columns one and three of Table 2, imparted negligible, if any, proportional changes to our coefficient estimates (which is logically consistent with the adding-up criterion). However, outside of these bounds, model parameter estimates fell sharply in absolute value and became statistically insignificant. For the empirical results discussed below, we interpret the Table 2 column two estimates with assumed direction vector (1,-1). This choice is further justified based simply on units of measurement, as the (1, -1) translation ratio in standard deviation terms reflects tradeoffs in percentile terms between the good and bad child outcomes. That is, percentile changes associated with one standard deviation changes in BPI or BMI_HIGH match the percentile changes associated with one standard deviation changes in PREAD or PMATH.

Turning first to the outcome variables, Table 2 results indicate that children's math, reading, BMI_HIGH, and BPI outcomes exhibit significant jointness. Nearly all Table 2 outcome coefficients, including outcome interactions and squares, are statistically significant with p-values at or below 10 percent. Given the quadratic relationship between outputs in our empirical model (and the implicit function rule), the marginal effect of any output (or input) upon another outcome is a function of several outcome variables. Since all outcome variables are standardized with zero mean, calculation of marginal effects for the "average" sample child is straight forward as all output variables in the marginal effects function equal zero. However, it is also possible to compute marginal effects for different child subsamples of interest. For these subsample groups we utilize the automated utility in TSP to calculate marginal effects. These calculations are based upon the outcome means (in standardized terms) specific to that child subsample. We calculate marginal effects using our full 759 observation sample and compare these to four child subsamples: above [below] average children (N = 389[370]) whose combined PMATH and PREAD scores are above [below] the full sample mean; healthy weight children (N = 522) whose BMI_HIGH =0; overweight children (N = 237) whose BMI_HIGH > 0; and children with "some behavior problems" (N = 327) whose BPI score exceeds the full sample mean.

For the average (full) sample child, computed partial effects of PMATH and PREAD on BPI are negative, suggesting that improvements in math and reading performance are associated with reduced BPI scores. These partial effects remain positive but diminish for above average sample children. For below average children, improvements in math and reading performance also reduce BPI but to a much larger degree than among the average and above average children. These findings are far more extensive than anything found in the child-development literature, but are still consistent with it. For example, Farrington (1987) and Werner (1989) find an elevated frequency of various child social and behavior problems among groups of children who exhibit lower than average academic achievement.

Our results indicate a few noteworthy interactions between BMI_HIGH and other outcomes. First, among our full sample and all subsample child groups (including children with some behavior problems), we find no evidence of a positive link between child weight gain (into overweight status) and increased behavior problems. However, we do find that child weight gain associates with reduced child math performance for our full sample, and also for the above average and healthy weight subsample groups. And, among the above average children, movement towards overweight status associates with reduced reading as well as math performance. Our coefficient estimates further suggest that the negative impact of BMI_HIGH on PMATH and PREAD scores diminishes as a child's weight status increases. In particular, among the subsample of children who are overweight, further weight gain does not appear to reduce math or reading performance, nor does it increase behavior problems.

Table 2 coefficients for HEADSTART_1YR suggest that participation for at least one year in a Head Start program raises PREAD and PMATH scores and lowers BPI and BMI_HIGH. On average, one year or more of Head Start raises PREAD and PMATH scores by about 0.21 of a standard deviation. This effect is lower (0.11) for above average children, and is higher (0.35) for below average children and for overweight children (0.31). The coefficients for NBRATE_URBAN are positive and significant, implying that children whose parents attach a higher rating to the quality of their urban neighborhood environment exhibit higher (lower) PMATH and PREAD (BPI and BMI_HIGH) scores.[6] There is weak evidence of a positive (negative) association between frequency of meals eaten together as a family and higher (lower) child math and reading (BPI and BMI_HIGH) scores. There is also weak evidence of a positive (negative) association between nonschool recreation center visitation and higher (lower) child math and reading (BPI and BMI_HIGH) scores. The marginal impacts of both MEALS and SUM_REC are slightly smaller (larger) for the healthy weight (overweight) child subsamples. Finally, presence of a mobility limiting child health condition imparts a negative impact on math performance, but not on reading performance. And, at least for this sample, mobility limitations do not appear to increase children's BMI_HIGH or BPI.

[6] Because our neighborhood quality covariate is not invariant to monotonic transformations, possibly implying different parameter values across respondent mothers, we do not calculate the magnitudes of the impacts of neighborhood quality improvements upon children's good and bad outcomes. However, the estimated signs of these impacts are valid because any transformation preserves the rankings.

A persistent and strong pattern emerging across all Table 2 specifications is the significance of baseline HOME quality for ages 0-5 years. Of any input, HOME exerts the strongest positive (negative) impact on math and reading (BPI and BMI_HIGH) outcomes. On average, a 10 percent increase in HOME improves child reading (math) performance by almost 22 percent (25 percent), and reduces BPI (BMI_HIGH) by almost 40 percent (30 percent). Consistent with Todd and Wolpin (2007), the HOME index quality measure exerts a positive and highly significant impact on children's PREAD and PMATH scores in their later lives; however our estimated marginal impacts are more than six times greater than those estimated by Todd and Wolpin (2007), and by Blau (1999). We attribute this result to our empirical methodology treating child inputs and outcomes as jointly determined rather than strongly separable. Since the quality and type of children's activity engagements make up part of the overall HOME index score, the dominance of HOME in Table 2 further suggests that children raised in higher quality home environments are more likely to engage in regular physical activities and/or less likely to engage in unsupervised, sedentary activities. In relation to other Table 2 inputs, the marginal impact of HOME on SUM_REC (HRS/W_TV) is positive (negative), suggesting that HOME is jointly positively (negatively) associated with model inputs representative of sample children's active (sedentary) behaviors. Thus, as in Strauss and Knight (1999) and others, increased hours of television viewing, itself, serves as a weak predictor of children's propensity to gain excess body weight; instead, children with higher HOME scores reveal significantly lower rates of overweight even after accounting for the amount of television viewing or other sedentary activities. Increased television viewing plausibly serves as in indicator of overall low physical activity among children whose parents supply them with low physical, mental, and social stimulation for which their low HOME index scores affirm.

Table 3 displays estimated technical efficiencies in decimal percentage terms for the (2, -1), (1, -1), and (1, -2) direction vectors. Technical efficiencies are calculated using expression (2.10). If we assume a (1,-1) direction vector (middle of this Table), the technical efficiency of the average 1996 household is about 0.76. According to this measure, if this average household were to utilize its observed child care inputs as effectively as the best practice household, then its production of good (bad) child outcomes would increase (decrease) by about 32 percent (1/0.76) = 1.32. Stated in terms of total costs to achieve a given level of output, if constant returns-to-scale prevail, the average sample household could attain its 1996 level of effectiveness at 32 percent less cost.[7] Between 1996 and 2000, average household technical efficiency declines slightly from 0.76 to about 0.74. If we change our assumed direction vector to (2, -1), average 1996 technical efficiency increases slightly to 0.83 (row one in Table 3).

Table 4 reports computed PC, TC, and EC according to sample child age. Rather than aggregate panel children by interview wave, Table 4 aggregates them by current age, whatever the interview wave. Table 4 figures are calculated as follows. The value of $\hat{D}_o^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it})$ is estimated for each age from 7 through 13 years. Then, for each age, EC is computed using (2.18), TC using (2.19), and PC using (2.20). Since some sample children were not yet 7 years old as of the 1996 interview wave, children who were 6.75 to 6.99 years in 1996 were treated as being in their 7th year. Table 4 computations represent year-to-year percentages of PC, TC, and EC in decimal terms. Direction vectors (2, -1) and (1, -1) produce very similar results; the (1, -2) direction produces slightly lower averages. Referring to the (1,-1) estimates in the middle of this Table, three features are notable. First, TC, which measures the outward shift in the production frontier, averages

[7] Studies of technical inefficiency in private sector firms, public schools, and public utilities estimate inefficiencies at or above this level. See, for example, Schmidt and Sickles (1984), Grosskopf et al. (1997), and Atkinson and Primont (2002).

approximately 6 percent annually, peaking at children's age 8 and declines steadily (from about 10.8 percent to zero) as age increases. Second, EC, which measures children's catching up to the frontier, is positive and declining for children's ages 7 to 9, and is negative and declining thereafter. Third, the resulting PC (the sum of TC and EC) attains a maximum at children's age 8, and steadily declines and eventually turns negative for ages 12-13. Thus the decline of both TC and EC contribute to falling PC among sample children.

The outward movement of the production frontier that occurs with child age coupled with declining productivity change highlights two important features widely acknowledged in the child development literature. First, maturation plays an important role in our sample children's overall development (i.e., outward shifts of children's production possibilities occur to a large degree with age). This is evidenced by the marginal impact of child age on child outcomes in Table 2. Roughly equivalent across each assumed direction vector, the Table 2 estimated coefficients for child age predict an approximate 2.1 (2.0) percent increase (decrease) in good (bad) outcomes for every 1 percent increase in child age. This marginal impact is close in magnitude to the marginal impact of HOME on child outcomes, which is not trivial.[8] Second, rising, and then declining productivity change suggests that parents' input productivity is highest during their children's younger ages. This too is consistent with a wide body of literature (e.g., Scarr and Weinberg, 1983) asserting that younger children are more malleable to changes in their family environments and circumstances than are older children who enjoy greater autonomy.

[8] The child development literature recognizes maturation as a fundamental component of cognitive and social development (Ruffin, 2001). Biological maturation enables children with ever-expanding abilities (e.g., brain and nervous system maturation improves cognitive and motor skills necessary to expand reading, writing, and complex thought capabilities). Maturational patterns can vary widely across children even of the same age.

4. Conclusions

This study developed a household production model in which the household's production technology is characterized as a multiple-output directional distance function. The directional distance function is useful for estimating complex interrelationships between jointly produced outcomes within households because it readily handles the case of estimating multiple endogenous outcomes without the need to specify and identify simultaneous equations systems, or to resort to estimation of reduced forms. Using a balanced panel of 253 families from the National Longitudinal Survey of Youth-Child Sample spanning 1996 to 2000, we evaluate parents' joint production of four plausibly interrelated child outcomes, reading and math performance, behavior problems, and excessive body weight gain. We use a fixed-effects, within estimator with instrumental variables to control for time-invariant and time-variant unobservables. A bootstrap method is applied to correct for bias caused by weak instruments for two of the endogenous inputs.

We find no evidence of a positive association between excessive child weight gain and increased behavior problems among sample children. Also not present is any significant association between children's weight gain their amount of television viewing time. However, our results indicate a significant association between children's weight gain and reductions in their reading and math performance. The magnitudes of these negative impacts vary to some extent among the different child subsamples examined. We find that a better home and (parent perceived) neighborhood environment, Head Start participation, and increased time spent together during family meals improve children's reading and math skills as well as reduce their behavior problems and overweight status. Finally, children's cognitive/behavioral productivity growth is found to be highest at the sample child age of 8, but diminishes thereafter; suggesting that home and neighborhood contributions to child outcomes weaken as children approach adolescence.

Several messages for policy emerge from this study. First, the complementarities we observe among our sample children's math and reading skills suggests that encouraging children to excel in subjects for which they demonstrate a comparative advantage can yield spillover effects beneficial to a child's non-comparative-advantage skills. Second, maturation clearly influences child development. Our model and data suggest that productivity of observed home and neighborhood inputs peak at early child ages and decline into adolescence. More research is needed to determine whether returns to government subsidies of child inputs are highest if directed toward families with younger children or children of a specific age. Also, since our sample households exhibit considerable technical inefficiency in their production of child outcomes, improvements in parents' technical efficiencies, possibly through educational/training programs, could result in substantial gains in their production (reduction) of good (bad) outcomes. Finally, children's everyday lives take place in their homes and in their immediate neighborhoods. Our results clearly suggest that the quality of these environments matter to children's mental and physical development; they are at least as important as their biological maturation. Policies aimed at enhancing the physical and mental well-being of children should pay close attention to the characteristics of the areas in which people live as well as the characteristics of the people who live in these areas.

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Table 1: Variable Means (Std. Dev.) by Year (N=253; T=3)

Year	1996	1998	2000
Outputs:			
BMI_HIGH (> 85th percentile for age and gender)	0.78 (1.93)	1.06 (2.44)	1.71 (3.63)
BPI (total raw score)	81.57 (58.41)	77.55 (58.66)	66.18 (51.48)
PIAT_MATH (total raw score)	35.13 (11.08)	47.30 (9.87)	54.15 (10.58)
PIAT_READ (total raw score)	36.89 (11.77)	49.11 (12.02)	58.94 (13.10)
Home Inputs:			
HRS/D_HMWK (daily hours on homework)	0.02 (0.12)	0.02 (0.11)	0.01 (0.09)
HRS/D_MEALS (daily hours with family)	0.02 (0.12)	0.02 (0.11)	0.01 (0.09)
HRS/D_READ (daily hours reading)	0.91 (0.28)	0.93 (0.26)	0.93 (0.25)
HRS/W_TV (weekly hours TV)	0.91 (0.28)	0.93 (0.26)	0.93 (0.25)
HS_1YR (1+ years in Headstart)	0.08 (0.27)		
NBHD_QUAL (5=best, 1=worst)	2.23 (1.10)	2.19 (1.09)	2.12 (1.07)
OUTSCH_REC (regular activity)	0.01 (0.09)	0.38 (0.49)	0.36 (0.47)
URBAN (residence; yes=1, 0=no)	0.71 (0.46)	0.58 (0.49)	0.61 (0.49)
Child Characteristics:			
AGECH (years)	8.41 (0.89)	10.41 (0.89)	12.41 (0.89)
HEALTH_MOBILITY (limits physical activity)	0.02 (0.14)	0.02 (0.15)	0.04 (0.20)
HEIGHT (inches)	51.77 (3.62)	56.48 (3.86)	61.32 (4.0)
HMWK_FREQ (homework days/week)	3.33 (1.58)	3.84 (1.21)	3.84 (1.16)
MSD (total raw score)	10.46 (2.59)		
NUMCHILD (age 18 years or less)	2.34 (0.82)	2.36 (0.87)	2.26 (0.88)
PPVT-R (total raw score)	82.18 (14.43)		
TMP (total raw score)	69.73 (13.73)		
Parent Characteristics:			
AFQT (mother's total raw score)	47.70 (26.37)		
BLACK (yes=1, no=0)	0.18 (0.39)		
CATHOLIC (mother is Catholic; yes=1, no=0)	0.42 (0.49)		
DADPRSNT (dad lives at home; yes=1, no=0)	0.70 (0.46)	0.70 (0.46)	0.66 (0.48)
EDUC_FATH (grandfather's years)	10.95 (3.53)		
EDUC_MOTH (grandmother's years)	11.10 (2.59)		
HISPANIC (yes=1; no=0)	0.15 (0.35)		
INCOME (ten thousands)	6.47 (3.20)	5.65 (3.32)	6.15 (5.01)
MOMAGE (years)	30.86 (2.04)	32.86 (2.04)	34.86 (2.04)
MOMEDUC (mother's years)	13.53 (2.08)		
MOMWAGE (monthly)	1172.61 (842.32)	1189.13 (601.83)	1387.91 (770.21)
MOMWKHRS (average daily)	7.68 (2.09)	7.77 (1.82)	7.75 (2.22)

Table 1 (Continued)

Year	1996	1998	2000
Community Variables:			
API (county air pollution index)	31.4 (10.3)	33.2 (9.7)	38.2 (13.2)
CRIME (per 10^7 population)	478.0 (234.2)	485.6 (235.6)	483.2 (241.4)
FHEAD (county in 10^3)	26.98 (62.07)	33.52 (71.64)	30.52 (64.70)
PHYSICIANS (per 10^7 population)	159.1 (103.1)	161.8 (100.0)	159.8 (100.8)
POPULATION (county in 10^7)	63.0 (135.5)	72.9 (155.6)	65.6 (137.0)
PRICE_CIGS (cents/pack)	187.57 (25.01)	219.88 (27.13)	341.02 (39.25)
PT_RATIO (state public and private)	17.26 (2.40)	16.47 (2.16)	16.04 (2.16)
T_SALARY (thousands)	37.98 (6.40)	39.86 (6.24)	42.25 (5.64)
UNEMPL (% county)	6.93 (3.07)	5.39 (2.95)	4.85 (2.71)

Table 2: Directional Distance Function Estimates

Variable	Coefficient (Asy. t-value)		
	$g_y = 2; g_{\tilde{y}} = -1$	$g_y = 1; g_{\tilde{y}} = -1$	$g_y = 1; g_{\tilde{y}} = -2$
Outputs:			
PREAD	-0.35893 (-3.9390)**	-0.40688 (-2.8313)**	-0.15488 (-1.6199)
PMATH	0.09169 (1.1079)	0.14044 (1.1297)	0.06355 (0.7429)
BPI	0.31964 (3.5614)**	0.50308 (3.9213)**	0.29971 (3.8911)**
BMI_HIGH	0.14588 (1.8529)*	0.23049 (1.9776)**	0.15462 (2.1259)**
PREAD–Squared	0.41085 (8.2370)**	0.75609 (7.5401)**	0.56935 (6.3105)**
PMATH–Squared	0.18700 (1.9417)*	0.45357 (4.1475)**	0.45728 (4.1839)**
BPI–Squared	-0.15856 (-3.1560)**	-0.21551 (-3.1272)**	-0.10760 (-3.0129)**
BMI_HIGH–Squared	0.02378 (0.7742)	-0.01504 (-0.4739)	-0.04034 (-2.3018)**
PMATH*PREAD	-0.29453 (-3.1312)**	-0.80948 (-11.5747)**	-0.82199 (-5.7638)**
BPI*PREAD	-0.02977 (-0.2900)	-0.23322 (-1.6456)*	-0.12344 (-1.8528)*
BMI_HIGH*PREAD	0.06560 (1.2336)	0.17983 (1.5793)	-0.01151 (-0.1360)
BPI*PMATH	-0.10543 (-1.0335)	-0.07166 (-0.5125)	-0.10248 (-1.4564)
BMI_HIGH*PMATH	-0.10963 (-1.8604)*	-0.28425 (-2.5120)**	-0.07988 (-1.0997)
BMI_HIGH*BPI	-0.11184 (-2.6460)**	-0.08937 (-1.7568)*	-0.00536 (-0.1834)

Note: ** (*) denotes significance at the .05 (.10) level using a two-tailed asymptotic t-test.

Table 2 (Continued)

Variable	Coefficient (Asy. t-value)		
	$g_y = 2; g_{\tilde{y}} = -1$	$g_y = 1; g_{\tilde{y}} = -1$	$g_y = 1; g_{\tilde{y}} = -2$
Parent Inputs:			
HEADSTART_1YR*AGECH	0.05509 (1.8499)*	0.09579 (2.0858)**	0.06578 (2.1492)**
HOME	0.04609 (1.8188)*	0.09792 (2.4952)**	0.08103 (3.3105)**
HRS/D_MEALS*AGECH	0.03648 (2.1053)**	0.02938 (1.2268)	0.00114 (0.0761)
MOMWKHRS*AFQT	0.00289 (0.0747)	0.02483 (0.4564)	0.01853 (0.5611)
NBHD_QUAL*URBAN	0.01398 (1.6389)*	0.02648 (2.1803)**	0.01648 (2.1324)**
Child Inputs:			
HEALTH_MOBILITY	0.07990 (2.0085)**	0.10421 (1.7442)*	0.01615 (0.4622)
HRS/D_HMWK*AGECH	-0.01108 (-0.6348)	0.00435 (0.1695)	0.02346 (1.4089)
HRS/D_READ*AGECH	-0.01637 (-0.9684)	-0.03001 (-1.2405)	-0.02015 (-1.3364)
HRS/W_TV*AGECH	0.01905 (0.7847)	0.02770 (0.8371)	0.00913 (0.4540)
OUTSCH_REC*AGECH	-0.03537 (-1.6524)*	-0.02694 (-0.8622)	-0.00548 (-0.2644)
Time:			
AGECH	0.18005 (3.8779)**	0.18005 (2.1978)**	0.05608 (0.9347)
AGECH–Squared	-0.00752 (-4.2990)**	-0.00782 (-2.4751)**	-0.00245 (-1.0708)

Note: ** (*) denotes significance at the .05 (.10) level using a two-tailed asymptotic t-test.

Table 3: Average Child Technical Efficiencies

Year	Technical Efficiency Score Mean	Std. Dev.
	Direction: $g_y = 2, g_{\tilde{y}} = -1$	
1996.	0.82804	0.05626
1998.	0.82669	0.05189
2000.	0.78135	0.06063
	Direction: $g_y = 1, g_{\tilde{y}} = -1$	
1996.	0.76051	0.07117
1998.	0.77834	0.06503
2000.	0.73872	0.07270
	Direction: $g_y = 1, g_{\tilde{y}} = -2$	
1996.	0.76277	0.06643
1998.	0.73874	0.05892
2000.	0.69474	0.06656

Table 4: Age Varying PC, TC, and EC

Child Age	PC	TC	EC
	Direction: $g_y = 2, g_{\tilde{y}} = -1$		
7.	0.09997	0.08888	0.01109
8.	0.09952	0.10177	-0.00225
9.	0.07048	0.07755	-0.00707
10.	0.03290	0.05478	-0.02189
11.	-0.05325	-0.00636	-0.04690
12.	-0.07871	-0.03408	-0.04464
Avg.	0.02848	0.04709	-0.01861
	Direction: $g_y = 1, g_{\tilde{y}} = -1$		
7.	0.11950	0.08574	0.03376
8.	0.12107	0.10751	0.01356
9.	0.09589	0.08410	0.01179
10.	0.06370	0.07350	-0.00980
11.	-0.01663	0.02357	-0.04020
12.	-0.03797	-0.00078	-0.03719
Avg.	0.05759	0.06227	-0.00468
	Direction: $g_y = 1, g_{\tilde{y}} = -2$		
7.	0.01512	0.02790	-0.01278
8.	0.01973	0.05056	-0.03083
9.	0.01448	0.03896	-0.02448
10.	0.01399	0.04825	-0.03426
11.	-0.00770	0.03546	-0.04316
12.	-0.01208	0.02850	-0.04058
Avg.	0.00726	0.03827	-0.03102