

Multiple-Output Child Health Production Functions: The Impact of Time-Varying and Time-Invariant Inputs

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Many production activities generate undesirable outputs in conjunction with the desirable outputs. In this paper we present the first estimates of a multiple-input, multiple-output directional distance function that relates good and bad inputs from home, school, and environment to good and bad outputs, measured as children's cognitive and behavioral development. This household directional distance function is estimated using a balanced panel of 369 families from the National Longitudinal Survey of Youth-Child Sample for 1996 to 2000 using the generalized method of moments within estimator and instrumental variables. We recover consistent partial effects for the time-invariant variables in a second-stage regression and estimate their corrected asymptotic standard errors. We then compute and examine productivity differences among households defined as the increase (decrease) in good (bad) outputs that families could attain with constant inputs if they were operating on the technological frontier. Our estimates suggest the presence of significant inefficiency among sample families that diminishes over time.

JEL Classification: C33, D13, I12

1. Introduction

In this paper 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. The last decade has witnessed increased concern with the impact of public policies and private investments on child health, perhaps motivated by an increased concern for equity and an enhanced recognition that human capital formation in children contributes significantly to society's future well-being. Children live in households with parents or adults who combine their skills with good as well as bad inputs that produce good as well as bad child health outcomes: physical, behavioral, and cognitive. A good input could be the time spent reading to a child, while a bad input could be parental smoking near a child. A good outcome could be higher reading skills, while a bad outcome could be a child's ill-health.

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Three features distinguish our modeling approach to the household production of child outcomes. First, we argue that multiple good and bad inputs can affect multiple measures of good and bad outcomes for children. Ignoring this by estimating single-equation relationships produces omitted variable bias and fails to model the tradeoffs among inputs and outcomes. To examine jointness among several good and bad outcomes as well as inputs and allow for heterogeneity among households in the productivity of observed child inputs, we specify and estimate an output-based directional distance function (Chambers, Chung, and Färe 1998) for a balanced panel of households with coresident children. This function allows us to estimate the maximum expansion of goods and the contraction of bads subject to a given level of observed inputs for a household using the underlying joint technology.

Second, we argue that households will produce child health with varying degrees of effectiveness. The “best practice” household is defined as that household that cannot make further increases in all good dimensions of child health and reductions in all bad dimensions by some additive amount, using a given level of observed inputs. This household practices its child care on the production frontier. Households within this frontier make less efficient use of personal and marketed child care inputs. Thus, we estimate the technical efficiency for household units in producing multiple outputs from multiple inputs.

Finally, 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 a jackknife technique.

The next section presents background for our hypotheses of (i) jointness in the household production of child health outcomes and (ii) the presence of technical inefficiency among households in the production process. In section 3, we discuss properties of the directional distance function and the calculation of partial effects. Results are presented in section 4, and conclusions follow in section 5. We find that some time-varying as well as time-invariant inputs are significant determinants of child health outcomes. The latter are nearly always overlooked in a fixed-effects analysis. Further, we find that the good child outcomes can be individually increased on the production frontier only with an increase in a bad outcome, that the average sample household using a given child health production technology falls short of the “best practice” household by approximately 1.5 standard deviations, and that this household inefficiency diminishes over the time range of our panel.

2. Background

The household production model (Becker 1965; Lancaster 1966) is the theoretical workhorse for economists studying household members’ behavior, well-being, or both. When applied to health issues, the model emphasizes that relative prices and incomes, along with biological processes, condition members’ health input choices (Rosenzweig and Schultz 1983). Applications often posit a cooperative agreement among adult members about a household utility function to be maximized subject to a full income constraint determined by members’ pooled resources (e.g., Jacobson 2000). This household utility function includes parent and child health as outputs of production functions whose endogenous inputs include members’ time and purchased goods and services as well as exogenous or predetermined endowment and

environmental factors (e.g., Grossman 1972). The literature applying this model has either 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 estimated “reduced form” production functions employing a common set of presumably predetermined or exogenous inputs (e.g., Blau 1999). We attempt to model systematically the jointness of health outcomes and endogeneity, as well as the differing efficiencies among households.

Jointness

The biomedical and the economics literature agree that human health, including child health, is multidimensional. For example, Blau (1999) assesses the impact of parental income on six child outcome measures involving cognitive skills, behavioral problems, and motor and social development using data from the National Longitudinal Survey of Youth. Dawson (1991) assesses 17 outcome measures, many of which are constructed from multiple items referring to children’s physical health, emotional well-being, and behaviors inventoried in the 1988 National Health Inventory Survey. A wide variety of children’s health outcomes are considered in the Browning (1992), Haveman and Wolfe (1995), and Thornton (2001) reviews of child quality production functions. Many of these child health outcomes are plausibly produced jointly because of technical interdependencies. For example, by giving their children more time and attention, parents might enhance their children’s cognitive skills and their good behavior. Playing video games may help a child’s hand and eye coordination while impeding his social development, or watching television may aid his verbal memory and acuity while making him obese. Readily noticed examples of this sort would seem to justify estimating child health outcomes jointly rather than independently.

Heterogeneity

Operation on the production frontier is a necessary condition for utility maximization in the household production model. However, there is abundant reason to believe that parents do not always have the requisite skills to maximize utility or that a child will be receptive to operating on his health production frontier. Even though firms are continuously subjected to the pressures of pricing and innovation from rivals, they frequently perform at less than the “best practice” production level for their industry.¹ If firms frequently fall short of best practice, it is likely that households will also. This may be due to adult heads of household who optimize individual utility rather than all members’ aggregate utilities (Lundberg and Pollak 1993; Fehr and Tyran 2005).² Further, parents’ efforts to understand the effects of inputs on child health outcomes and the synergies among such outcomes can be costly (Stigler 1976; Heiner 1983). Overcoming a “lack of commitment” to the household stemming from a short time horizon, small assets and thus low gains from intrahousehold cooperation, or weak

¹ For abundant empirical evidence on the failure of firms to operate on production frontiers see the symposium in the June 2005 issue of the *Journal of Econometrics* and the references therein. Empirical evidence for informational and nonprice sources of intrahousehold shortfalls appears in Agee and Crocker (1994), Nelson (1994), Lee, Rosenzweig, and Pitt (1997), and Abrevaya (2001). Issues in the estimation of shortfalls due to strategic behaviors are reviewed in McElroy (1990).

² Because a child cannot enter into a binding forward contract to use the rewards of future earnings to compensate its parents for their prior investments in the child, parents have an incentive to underinvest in the child.

external enforcement of one's claims on household assets also prevent optimization of joint utility (Lundberg and Pollak 1993; Vagstad 2001). Whatever their source, many of these variables preventing optimization are unobservable.

However, an extensive empirical economics literature dealing with the effects of parental inputs on child health (e.g., Carlin and Sandy 1991; Agee and Crocker 1996) as well as public investment and safety programs on child health (Currie 2000; Kenkel 2000) universally posits household utility maximization subject to a two-sided random error term designed to reflect random unobservables. A one-sided error term reflecting random failure of inefficient households to reach the household production frontier is not modeled. The value-added specifications (Krueger 2000; Hanushek 2003) assume that by adding a lagged child outcome measure, one has included as a regressor all components of the one-sided error. The remaining error term is strictly two-sided. In explicit recognition of the presence of a one-sided error term, fixed-effect specifications have been employed to difference out time-invariant, family-specific unobservables from panel data (Blau 1999). A time-varying, one-sided error term can also be associated with these regressions.

3. The Directional Distance Function

Specification

Consider a household production technology where parents combine multiple good inputs, $\mathbf{x} = (x_1, \dots, x_N) \in R_+^N$, to produce multiple good outputs, $\mathbf{y} = (y_1, \dots, y_G) \in R_+^G$. The household's production technology, $S(\mathbf{x}, \mathbf{y}, t)$, can be written as

$$S(\mathbf{x}, \mathbf{y}, t) = \{(\mathbf{x}, \mathbf{y}) : \mathbf{x} \text{ can produce } \mathbf{y} \text{ at time } t\}, \quad (1)$$

where $t = 1, \dots, T$ is time. The technology must satisfy a set of basic axioms discussed in Färe (1988), including convexity of $S(\mathbf{x}, \mathbf{y}, t)$ for all \mathbf{x} and free disposability of inputs and outputs.

Production of "bad" outputs (e.g., a child's ill-health or behavioral problems) can be appended to Equation 1 simply by defining a vector of \mathbf{B} bads, $\mathbf{b} = (b_1, \dots, b_B) \in R_+^B$, which is produced jointly with \mathbf{y} . As in Pollak and Wachter (1975), joint production of bads in the production of goods can be a function of both inputs and outputs. Following Chambers, Chung, and Färe (1998), we define the output directional distance function as

$$\vec{D}_o(\mathbf{x}, \mathbf{y}, \mathbf{b}; \mathbf{0}, \delta_y, -\delta_b) = \sup\{\beta : (\mathbf{y} + \beta\delta_y, \mathbf{b} - \beta\delta_b) \in P(\mathbf{x})\}, \quad (2)$$

where $P(\mathbf{x})$ is the output set of goods and bads that can be produced with \mathbf{x} , and $(\delta_y, \delta_b) \neq (\mathbf{0}, \mathbf{0})$ is a direction vector. The output directional distance function increases (decreases) good (bad) outputs in the direction δ_y (δ_b) for a given level of observed inputs in order to move to the frontier of P . We interpret this function as a measure of the results of a household's shortfall due to unobservables in production of child health goods and reduction of bads relative to the best practice household. 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 .

Formally, among the important properties of the output directional distance function are the following:

$$\vec{D}_o(\mathbf{x}, \mathbf{y} + \alpha\delta_y, \mathbf{b} - \alpha\delta_b; 0, \delta_y, -\delta_b) \geq 0 \Leftrightarrow (\mathbf{y}, \mathbf{b}) \in P(\mathbf{x}), \quad (3)$$

$$\vec{D}_o(\mathbf{x}, \mathbf{y} + \alpha\delta_y, \mathbf{b} - \alpha\delta_b; 0, \delta_y, -\delta_b) = \vec{D}_o(\mathbf{x}, \mathbf{y}, \mathbf{b}; 0, \delta_y, -\delta_b) - \alpha, \quad (4)$$

$$(\mathbf{y}', \mathbf{b}) \leq (\mathbf{y}, \mathbf{b}) \in P(\mathbf{x}) \rightarrow \vec{D}_o(\mathbf{x}, \mathbf{y}', \mathbf{b}; 0, \delta_y, -\delta_b) \geq \vec{D}_o(\mathbf{x}, \mathbf{y}, \mathbf{b}; 0, \delta_y, -\delta_b), \quad (5)$$

$$(\mathbf{y}, \mathbf{b}') \geq (\mathbf{y}, \mathbf{b}) \in P(\mathbf{x}) \rightarrow \vec{D}_o(\mathbf{x}, \mathbf{y}, \mathbf{b}'; 0, \delta_y, -\delta_b) \geq \vec{D}_o(\mathbf{x}, \mathbf{y}, \mathbf{b}; 0, \delta_y, -\delta_b). \quad (6)$$

Equation 3 says that the output directional distance function will be nonnegative for all feasible output vectors. Equation 4 is the translation property, which is analogous to the property of linear homogeneity with a standard output distance function.³ Next, Equation 5 tells us that if output increases for a given level of bads and inputs, then technical inefficiency will decrease. Equation 6 is analogous to Equation 5: if bads increase for a given level of inputs and outputs, then technical inefficiency will increase.

Estimation

The output-oriented directional distance function measures each household's potential to increase good outputs and to reduce bad outputs for their children, subject to a given level of observed inputs. With the household survey data we employ in our empirical application, many of our observed inputs and outputs are either dichotomous or include zero. Although a quadratic is a flexible functional form, in preliminary estimates (available from the authors) we failed to reject the null hypothesis that the squared and interaction terms in a quadratic specification of $\vec{D}_o(\mathbf{x}, \mathbf{y}, \mathbf{b})$ are jointly equal to zero. Therefore, we restrict the quadratic form to a linear one:

$$\begin{aligned} \vec{D}_o(\mathbf{x}, \mathbf{y}, \mathbf{b}) = & \sum_{n=1}^N \beta_n x_n + \sum_{g=1}^G \gamma_g y_g + \sum_{w=1}^B \phi_w b_w \\ & + \sum_{t=1}^{\tau} \gamma_t d_t + \varepsilon_{it}, \end{aligned} \quad (7)$$

where

$$\varepsilon_{it} = (v_{it} - u_{it}), \quad (8)$$

so that ε_{it} is an additive error with a one-sided component, u_{it} , and a standard noise component, v_{it} , with zero mean, and d_t is a time dummy. To satisfy the translation property in Equation 4, one restriction is imposed:

$$\sum_{g=1}^G \gamma_g - \sum_{w=1}^B \phi_w = -1. \quad (9)$$

We satisfy Equation 3 after estimation via a normalization as discussed below.

³ Given that $\delta_y = \delta_b = 1$, this translation property implies that if a good outcome increases by $\alpha\delta_y$ while a bad outcome falls by $\alpha\delta_b$, then the distance function declines by α ; i.e., a household's child health production will be more effective by the amount α (Färe et al. 2005, p. 475).

Using panel data, we could estimate Equation 2 treating u_{it} , the one-sided error component representing unobserved heterogeneity, as either fixed or random. Use of a random-effects approach imposes the generally implausible assumption that the u_{it} are uncorrelated with included variables. Use of a fixed-effects approach sweeps out the time-invariant unobservables, so that our estimators are consistent even though we allow for nonzero correlation between them and the included variables. To recover the partial effects of the time-invariant variables, we employ a two-stage estimator. In the first stage, we compute the within estimator using time-demeaned data, which eliminates all time-invariant variables, such as those for sex, race, and mother's background. 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). We therefore employ a second-stage regression that allows us to recover consistent partial effects for the time-invariant variables. We adjust the second-stage estimated standard errors because they are based on first-stage estimated coefficients. Since the time-demeaned variables in the first stage are orthogonal to the time-invariant ones in the second stage, there is no omitted variable bias. To our knowledge, this approach has not been used before in the child health production literature.

Consider a panel data set comprised of F family units, $i = 1, \dots, F$, over T time periods, $t = 1, \dots, T$. Further, let the $(N \times 1)$ vector of inputs be divided into a time-varying and a time-invariant component, where $\mathbf{x}_{it} = (x_{1,it}, \dots, x_{M,it})$ is a $(M \times 1)$ vector of time-varying inputs and $\mathbf{z}_i = (z_{1i}, \dots, z_{Ki})$ is a $(K \times 1)$ vector of time-invariant inputs. Also let $\mathbf{y}_{it} = (y_{1,it}, \dots, y_{G,it})$ be a $(G \times 1)$ vector of good time-varying outputs, and $\mathbf{b}_{it} = (b_{1,it}, \dots, b_{B,it})$ be a $(B \times 1)$ vector of time-varying bads. We can then write the directional distance function as

$$0 = \vec{D}(\mathbf{x}_{it}, \mathbf{z}_i, \mathbf{y}_{it}, \mathbf{b}_{it}; 0, 0, 1, -1) + v_{it} - u_{it}, \tag{10}$$

where the one-sided term, u_{it} , measures the family-specific inefficiency. Using the above notation, our linear specification for the directional distance function in Equation 10 can be written as

$$\vec{D}(\mathbf{x}_{it}, \mathbf{z}_i, \mathbf{y}_{it}, \mathbf{b}_{it}) = \mathbf{x}_{it}\beta + \mathbf{z}_i\theta + \mathbf{y}_{it}\gamma + \mathbf{b}_{it}\phi. \tag{11}$$

Estimation proceeds in two stages. In the first stage, we eliminate time-invariant unobservables, \mathbf{z}_i , by time-demeaning our data and then estimating the within instrumental variable model. Substituting Equation 11 into Equation 10 and time demeaning yields the first-stage model

$$D_{it} - \bar{D}_i = (\mathbf{x}_{it} - \bar{\mathbf{x}}_i)\beta + (\mathbf{y}_{it} - \bar{\mathbf{y}}_i)\gamma + (\mathbf{b}_{it} - \bar{\mathbf{b}}_i)\phi + v_{it} - \bar{v}_i - (u_{it} - \bar{u}_i), \tag{12}$$

where the group means are defined as

$$\begin{aligned} \bar{\mathbf{x}}_i &= T^{-1} \sum_{t=1}^T \mathbf{x}_{it}, \bar{\mathbf{y}}_i = T^{-1} \sum_{t=1}^T \mathbf{y}_{it}, \bar{\mathbf{b}}_i = T^{-1} \sum_{t=1}^T \mathbf{b}_{it}, \\ \bar{v}_i &= T^{-1} \sum_{t=1}^T v_{it}, \text{ and } \bar{u}_i = T^{-1} \sum_{t=1}^T u_{it}. \end{aligned}$$

Further, $\bar{D}_i = \sum_{t=1}^T D_{it} = 0$, since $D_{it} = 0$ for each observation.

In the second stage, we recover the effects of the time-invariant variables that were differenced out of the first stage. This is accomplished by computing the residuals

$$\hat{\vartheta}_i = 0 - \bar{\mathbf{x}}_i\hat{\beta} - \bar{\mathbf{y}}_i\hat{\gamma} - \bar{\mathbf{b}}_i\hat{\phi}, \tag{13}$$

using first-stage coefficient estimates, $\hat{\beta}$, $\hat{\gamma}$, and $\hat{\phi}$, together with the group means of their corresponding variables. These residuals then become the left-hand-side of the second-stage regression, which is

$$\hat{\vartheta}_i = \mathbf{z}_i \delta + \xi_i, \quad (14)$$

where the \mathbf{z}_i are the time-invariant variables that were differenced out of the first-stage regression, and ξ_i is a random error term.

To estimate the technical inefficiency of each household, we proceed as follows. The fitted directional distance function equals the negative of the fitted composite error term, $\hat{\varepsilon}_{it}$ and as such, represents unobserved parental inefficiency at producing child health. By computing the within estimator we accomplished the same thing as if we had added $\vartheta_i d_i$ to Equation 11, where d_i is a dummy variable for the child i , and estimated this model. That is, computing the within estimator is equivalent to having estimated the following model:

$$0 = \vec{D}(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}, t) + \vartheta_i d_i + \varepsilon_{it}^*, \quad (15)$$

where we have subtracted $\vartheta_i d_i$ from the composite error term, which is now equal to $\varepsilon_{it}^* = v_{it} - u_{it} - \vartheta_i d_i$. Thus, we must recover $\hat{\vartheta}_i$ using Equation 14 and add $\hat{\vartheta}_i$ to the composite residual, ε_{it}^* , to obtain $\hat{\varepsilon}_{it} = \hat{v}_{it} - \hat{u}_{it}$. To strip away the noise term, \hat{v}_{it} , we then regress $-\hat{\varepsilon}_{it} = \tilde{\varepsilon}_{it} = \hat{u}_{it} - \hat{v}_{it}$ on a set of child dummies, time, time squared, and interactions of child dummies and time using

$$\tilde{\varepsilon}_{it} = \delta_0 + \delta_i d_i + \delta_t t + \delta_{it} t^2 + \sum_t \delta_{it} d_i t + \varphi_{it}, \quad (16)$$

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} .

We have not yet imposed the restriction in Equation 3. We do so after estimation for each i by subtracting the smallest \tilde{u}_{it} (a negative number) from each \tilde{u}_{it} so that each adjusted value of \tilde{u}_{it} , which we define as $\tilde{u}_{it}^{\mathcal{F}}$, is nonnegative: that is, for each i :

$$\tilde{u}_{it}^{\mathcal{F}} = \tilde{u}_{it} - \min_i(\tilde{u}_{it}), \quad \forall t. \quad (17)$$

Thus, $\tilde{u}_{it}^{\mathcal{F}} \geq 0$ is our measure of the technical inefficiency for each household. Larger values of $\tilde{u}_{it}^{\mathcal{F}} \geq 0$ indicate greater household productivity shortfalls. Because we are estimating a directional distance function, all point-to-point distances from inside the frontier to the frontier will be unit sensitive (i.e., all changes in one output or input relative to another must be measurable in like units). So as to allow consistent comparisons among all output and input marginal effects, continuous input and output measures in our empirical model are standardized to a zero mean and unit variance. Dichotomous variables are left unchanged. Thus, for example, the marginal impact of one input on an output is in standard deviations. Similarly, if a given family has a $\tilde{u}_{it}^{\mathcal{F}}$ equal to 1.0, its child could have good (bad) outcome values one standard deviation higher (lower) using the same quantity of inputs if this family operated on the “best practice” frontier.

To determine the effect of any variable on any other variable in the first stage, we invoke the implicit function rule. The change in one time-varying input with respect to another

is given by

$$\partial x_m / \partial x_{m'} = -\beta_{m'} / \beta_m, \quad \forall m, m'; m \neq m'. \quad (18)$$

Similarly, the change in an output with respect to a time-varying input is

$$\partial y_g / \partial x_m = -\beta_m / \gamma_g, \quad \forall m, g, \quad (19)$$

and the change in an output with respect to another output is

$$\partial y_g / \partial y_{g'} = -\gamma_{g'} / \gamma_g, \quad \forall g, g'; g \neq g'. \quad (20)$$

We can also relate a change in any second-stage variable to that of any first-stage variable by substituting Equation 13 into Equation 14 to obtain

$$-\bar{x}_i \hat{\beta} - \bar{y}_i \hat{\gamma} - \bar{\mathbf{b}}_i \hat{\phi} = \mathbf{z}_i \delta + \xi_i. \quad (21)$$

Rearranging and taking partial derivatives, we obtain the partial effect of any time-invariant input on any time-varying input as

$$\partial x_{mi} / \partial z_{ki} = -\hat{\delta}_k / \hat{\beta}_m, \quad \forall k, m. \quad (22)$$

Other derivatives can be similarly obtained.

4. Data, Estimator, and Empirical Results

Data

Our data come 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 their own children along with information on parental input use and a variety of child outcomes (Bureau of Labor Statistics 2003). The NLSY79 is a nationally representative sample of individuals who were age 14–21 as of January 1, 1979, with significant oversamples of blacks and Hispanics. 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. The NLSY79-CS is a sample of all children ever born to the women of the NLSY79. The survey collects 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 ability, social and behavioral attributes, and qualities of the child's home environment. Interviews have been conducted biannually since 1986.

Our analysis focuses on a balanced panel of NLSY79-CS children who were aged 70 to 119 months in 1996, 94 to 143 months in 1998, and 118 to 167 months in 2000. In each of the 1996, 1998, and 2000 interview waves, all of our 369 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 abilities in mathematics and oral reading and the ability to derive meaning from printed words, serve as our output measures of child cognitive achievements. As in Todd and Wolpin (2006), we use the raw individual test scores rather than age-adjusted or percentile scores to capture any changes in absolute achievement over time due to changes in child receptivity and the success of parenting skills and efforts. Our interest focuses exclusively on the 1996–2000 NLSY79-CS children in the 6-to-14 year-old age range because most of a child's fundamental reading and quantitative skills are developed within this range. Because child development is a cumulative process, our empirical model seeks to consider both current and historical inputs as potential determinants of test scores in 1996, 1998, and 2000. When combined with data on the baseline home input (discussed below), our panel provides reliable current and historical measures on each child's home, school, and community inputs. We estimate a balanced panel to facilitate the comparison of productivity measures over time.

Table 1 presents sample means and standard deviations for all variables we employ in each of the three interview waves. Our sample consists of 1107 observations on the 369 families having no missing data for the years 1996, 1998, and 2000. For two reasons this sample is considerably smaller than that used by previous studies (e.g., Blau 1999; Todd and Wolpin 2006) employing the NLSY79-CS. First, these studies estimated a series of single-equation, separable production functions so that deletion of missing observations on outputs (or inputs) not being considered was unnecessary. Second, they combined data for all available years, resulting in a large, though highly unbalanced, panel.⁴

Clearly, parents produce a broad range of good and bad child outcomes from a broad range of good and bad inputs; however, data and modeling limitations preclude estimation of an all-encompassing multiple-output directional distance function. To narrow the scope of our analysis, we estimate a cluster of three plausibly interrelated outputs of the home production process. In addition to our two good (PIATMATH and PIATREAD) time-varying outputs, we examine one time-varying bad, the child's Behavior Problems Index (BPI), which assesses wide-ranging behavioral problems as calculated from a series of questions on the frequency, range, and type of such problems as reported by the child's mother. More such problems increase the Index. The relationship between children's cognitive, behavioral, and health outcomes has been extensively examined in the literature (e.g., Hill and Stafford 1980; Shakotko, Edwards, and Grossman 1981; Brooks-Gunn, Guo, and Furstenberg 1993). For instance, low scores on measures of children's cognitive ability such as verbal IQ (Farrington 1987; Werner 1989) have been associated with behavior problems. While there is some disagreement as to the direction of the causality between cognitive ability and behavior problems (Martin 1976; McGee, Williams, and Share 1986; Yoshikawa 1994), some evidence suggests that cognitive deficits lead to problem behaviors and not vice versa (Moffit 1993).

We treat a number of time-varying inputs to the child outcome production process as endogenous to the parents: mother's daily work hours in her current paying job (MOMWKHRS); her daily number of cigarettes smoked (CIGARETTES); enrollment of the subject child in a private or religious school (PRIVSC) or in a public school (PUBSC); the child's age (AGECH), conditioned by whether or not the child ever attended Head Start (HSEVER); and annual household income (INCOME) per number of coresident children (NUMCHILD) age 18 or under.

⁴ If panel balance and missing observations were not at issue, our 1996–2000 sample could be increased from 369 to 2280 children.

Table 1. Variable Means (Standard Deviations) by Survey Year; $F = 369$ Families

Year	1996	1998	2000
Outputs:			
BPI (total raw score)	80.16 (59.24)	78.62 (59.96)	65.02 (52.60)
PIATMATH (total raw score)	32.06 (12.22)	44.68 (10.88)	52.64 (10.23)
PIATREAD (total raw score)	33.82 (12.73)	46.97 (12.86)	57.07 (13.50)
Inputs:			
API	31.95 (10.47)	33.28 (10.21)	38.47 (12.93)
CIGARETTES (daily)	3.54 (7.54)	3.29 (8.27)	3.46 (7.46)
HOME02	144.21 (19.48)		
School inputs:			
HSEVER	0.17 (0.38)		
PRIVSC	0.089 (0.19)	0.084 (0.20)	0.079 (0.21)
PTRATIO	17.22 (2.34)	16.44 (2.14)	16.05 (2.13)
PUBSC	0.897 (0.30)	0.905 (0.29)	0.911 (0.29)
TSALARY (thousands)	37.23 (6.17)	39.04 (6.01)	41.44 (5.48)
Child characteristics:			
AGECH (months)	96.61 (13.46)	120.61 (13.46)	144.61 (13.46)
ASTHMA	0.043		
BIRTHORDER	1.97 (0.98)		
BIRTHWT (ounces)	120.83 (21.06)		
BOY	0.52 (0.5)		
HEARDIFF	0.011 (0.10)		
LEARNDIS	0.008 (0.09)		
NUMCHILD	2.47 (0.94)	2.45 (0.91)	2.36 (0.93)
MSD (total raw score)	10.36 (2.35)		
TMP (total raw score)	64.36 (14.59)		
PPVT-R (total raw score)	71.15 (23.62)		
Parent characteristics:			
AFQT	47.03 (27.22)		
BLACK	0.23 (0.42)		
CATHOLIC	0.38 (0.49)		
EDUCFATH (years)	11.02 (3.57)		
EDUCMOTH (years)	11.17 (2.76)		
FORBORN	0.038 (0.19)		
HISPANIC	0.15 (0.36)		
INCOME (ten thousands)	5.86 (1.21)	5.71 (3.66)	5.71 (4.33)
LIVEBOTH	0.73 (0.45)		
MOMAGE (years)	34.78 (2.08)	36.78 (2.08)	38.78 (2.08)
MOMEDUC (years)	13.44 (2.17)		
MOMWAGE (hourly)	11.27 (8.10)	11.69 (6.68)	13.78 (9.30)
MOMWKHRS (daily hours)	7.63 (2.25)	8.02 (2.41)	7.78 (2.0)
Community variables:			
CRIME (per 10 ⁵ population)	4942.92 (2333.11)	5003.83 (2343.25)	4977.62 (2404.15)
PRICECIGS (cents/pack)	186.46 (25.77)	218.46 (27.97)	338.84 (39.86)
PHYSICIANS (per 10 ⁵ population)	1628.51 (1045.88)	1651.68 (1032.87)	1624.03 (1031.22)
UNEMPL (percent)	6.71 (3.0)	5.11 (2.77)	4.65 (2.56)

Exogenous time-varying inputs are the pupil/teacher ratio (PTRATIO) and average annual teacher's salary (TSALARY) in public and private elementary schools in the child's state of residence; the annual average air pollution index (API) in the child's county of residence; and dichotomous indicators for the 1996 (T1) and the 1998 (T2) interview waves.

Rationales for the construction and inclusion of these time-varying endogenous and exogenous variables follow. API and CIGARETTES are included because an impressive multidisciplinary chronicle of evidence links outdoor and indoor air pollution to child health and development problems. Currie and Thomas (1995, 2000) motivate the incorporation of AGECH \times HSEVER by their demonstration that the positive impacts of Head Start on child development can melt away with increased child age if continuing investments shrink substantially. INCOME/NUMCHILD is intended to capture potential maternal time and resource limitations. With more children, a mother has less time to interact individually with each child; a lower income makes the household less able to substitute market goods and services for maternal time. A lesser income together with more siblings increases the opportunity cost of devoting more maternal time and more household resources to the individual child. MOMWKHRS influences the wealth of opportunities the mother has to interact with her children. The variables PRIVSC and PUBSC are intended to register the influence of different ways of organizing the child's learning and socialization (excluded are home, other, or no schooling). PTRATIO and TSALARY speak to the quality of these learning and socialization settings.

In the second-stage regression, we estimate the impact of observable time-invariant parent, child, and household attributes that were differenced out in the first stage. All have been said at one time or another to be statistically significant or notable influences on children's cognitive and behavioral development. The variables BLACK and HISPANIC account for mother's and child's ethnicity. Whether or not the mother was born outside the United States (FORBORN), her mother's education (EDUCMOTH), her father's education (EDUCFATH), and whether or not she lived with both parents (LIVEBOTH) at age 14 plausibly say something about her cultural background and dynastic value system, and thus the skills and the effort she is able and willing to devote to child care. Time-invariant variables viewed as affecting the child's receptivity to health production inputs include child gender (BOY), whether or not the child has a hearing impairment (HEARDIFF), a learning disability (LEARNDIS), or asthma or any other chronic respiratory disorder (ASTHMA).⁵ Other such variables are the child's birth weight (BIRTHWT) and birth order (BIRTHORDER).

Last, the NLSY79-CS public use data contain an age-specific measure of each child's home environmental quality called the Home Observation Measurement of the Environment Short-Form, or HOME (Caldwell and Bradley 1984). The HOME index consists of four instruments that differ depending upon the age of the child: ages 0–2, 3–5, 6–9, and 10 and above. Information is collected both from maternal reports and interviewer observations on the overall quality of the child's home environment, maternal emotional and verbal responsiveness, maternal acceptance of and involvement with the child, orderliness of the home environment, presence of materials for child learning, activity variety, and stimulation. Questions asked of the mother differ somewhat across the four age ranges. In the empirical work reported below, we use the child's baseline home environment score administered at age 0–2 (HOME02) as our

⁵ The ethnicity of the mother is by definition the ethnicity of the child in the NLSY79-CS data. No children in our sample experienced a seeing impairment.

primary measure of the home environmental quality input. The total raw HOME02 score is a simple nonweighted sum of all individual items on the age 0–2-specific questionnaire (each item receives a 0 or 1 score).⁶

The instrument set for the first-stage Generalized Method of Moments (GMM) estimation includes a variety of variables. First, we include all of the exogenous time-demeaned variables in the first-stage regression (PTRATIO, TSALARY, AGECH, NUMCHILD, API, and T1 and T2), along with the squares of TSALARY and API. Because our panel had 1994 data available for both PUBSC and PRIVSC choice, we employed the lags of PUBSC and PRIVSC to strengthen our instrument set for school choice. We also include additional time-varying variables as instruments that are not part of stage one. These variables include the product of AGECH and each of the mother's general IQ measured by the Armed Forces Qualifying Test (AFQT), her years of education (MOMEDUC), along with EDUCFATH, FORBORN, and LIVEBOTH. Other mother-specific instruments include her hourly wage (MOMWAGE) if employed, and the product of her age (MOMAGE) and whether she is Catholic (CATHOLIC). Additional child-specific instruments include the product of AGECH and each of the 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), along with BIRTHWT, BLACK, HISPANIC, and BOY. Finally, additional residence-specific instruments include the price of cigarettes (PRICECIGS), crime rate (CRIME), physician numbers (PHYSICIANS), and unemployment rate (UNEMPL) of the household's county of residence, and the squares of these variables. While our choice of exogenous variables is somewhat *ad hoc*, our final choice was determined as that set which passed the *J* test for overidentification, as described below.

It is clear that all second-stage explanatory variables are predetermined from the family's point of view. Although it is possible that some of them are still correlated with the second-stage error, we are unable to find instruments that are arguably not endogenous and not weak instruments. Thus, we do not employ instruments in the second-stage estimation.

We now proceed to test the validity of our overidentifying restrictions and the strength of our instrument set for the first stage. We test the former using Hansen's (1982) *J* test, obtaining a test statistic of 18.68 with a prob value of 0.466, clearly failing to reject the null hypothesis of zero correlation of our overidentifying instruments with the error term. Although the simple cross section correlations between our endogenous covariates and the instruments is quite strong, the regressions of each time-demeaned endogenous variable on the full instrument set yield *F* statistics below 10 for three endogenous variables. Further, comparison of estimates from the instrumented and noninstrumented within models suggested presence of weak instruments (see, e.g., Cameron and Trivedi 2005).⁷

Because we have exhausted our set of feasible instruments, we employ the jackknife two-stage-least-squares (JK2SLS) estimator of Hahn and Hausman (2003) to correct for the bias caused by weak instruments. Formulas for the jackknife bias correction and jackknife estimator of the estimated coefficient standard errors are given in Shao and Tu (1995). To compute the jackknife bias correction for the estimated first-stage coefficients, let $\hat{\beta}$ be the estimator of β for

⁶ Missing observations for numerous variables precluded following our sample children back to their birth. Also, the biannual nature of the NLSY79-CS survey and the change in format of the home scale before age 6 and after age 9 precluded using a time-varying measure of HOME.

⁷ The noninstrumented within estimates are available from the authors.

Table 2. First-Stage Estimation: Time-Demeaned Variables with Instruments

Variable	Coefficient (Asy. <i>t</i> -Value)	
	No Bias Correction	Bias Correction
Outputs:		
IPIATREAD	-0.3563 (-3.4338)**	-0.4651 (-2.3844)**
PIATMATH	-0.2519 (-2.2713)**	-0.0361 (-0.1603)
BPI	0.3918 (6.5070)**	0.4988 (3.9401)**
Inputs:		
CIGARETTES	-0.0791 (-0.2752)	0.0502 (0.1017)
PTRATIO	-0.0489 (-1.2612)	-0.0687 (-1.0190)
TSALARY	-0.0048 (-0.1069)	-0.0177 (-0.2288)
AGECHHSEVER	-0.0406 (-1.6882)*	-0.0572 (-1.1149)
INCOMEDIVNUMCHILD	0.0264 (0.9814)	0.0246 (0.3284)
MOMWKHRS	0.0593 (1.0166)	0.0953 (0.8335)
API	0.0356 (1.6551)**	0.0488 (1.2725)
PUBSC	0.2656 (2.4158)**	0.5382 (2.9306)**
PRIVSC	0.1596 (2.3877)**	0.2946 (2.2685)**
Time:		
T1	-0.9335 (-9.6283)**	-0.7856 (-4.0615)**
T2	-0.4424 (-11.3600)**	-0.4097 (-5.6765)**

Asymptotic *t*-statistics in parentheses are computed using the corrected standard errors.

* $p < 0.1$

** $p < 0.05$

a sample of size n . First compute n jackknife estimates of β obtained by successively dropping one observation and recomputing $\hat{\beta}$. Call each of these i estimates $\beta_{J,i}$, $i = 1 \dots, n$, and their average $\bar{\beta}_J = \sum_{i=1}^n \beta_{J,i}$. Define the jackknife bias estimator as

$$\text{BIAS}_J = (n - 1)(\bar{\beta}_J - \hat{\beta}). \quad (23)$$

Then the jackknife bias-adjusted (BA) estimator of β is

$$\hat{\beta}_{BA} = \hat{\beta} - \text{BIAS}_J = n\hat{\beta} - (n - 1)(\bar{\beta}_J). \quad (24)$$

The intuition is that since we do not know β , we treat $\hat{\beta}$ as the “true” value and determine the bias of the jackknife estimator relative to this value. We then adjust $\hat{\beta}$ by this computed bias, assuming that the bias of the jackknife estimator relative to $\hat{\beta}$ is the same as the bias of $\hat{\beta}$ relative to β .

Empirical Results

Column 1 of Table 2 reports GMM instrumental variable estimates of the first stage of our output-based frontier directional distance function. Column 2 reports the bias-corrected estimates utilizing the JK2SLS bias correction and jackknife estimated standard errors. Table 3 presents ordinary-least-squares estimates for the time-invariant covariates comprising our second stage. All estimated standard errors for coefficients in Tables 2 and 3 were computed using the heteroskedastic-consistent covariance estimator of Newey and West (1987). In the first stage (Table 2), degrees of freedom lost from using time-demeaned data necessitate the upward standard error adjustment. Because standard errors of second-stage (Table 3)

Table 3. Second-Stage Estimation: Time-Invariant Variables

Variable (Parent and Child Characteristics)	Coefficient (Asy. <i>t</i> -Value)	
	No Bias Correction	Bias Correction
BLACK	-0.0372 (-0.7220)	0.0019 (0.0304)
HISPANIC	-0.0312 (-0.4227)	0.0445 (0.4748)
BOY	0.0197 (0.6038)	0.0176 (0.4605)
HEARDIFF	-0.0477 (-1.1977)	-0.0310 (-0.6948)
LEARNDIS	-0.0725 (-2.0828)**	-0.0689 (-1.6453)*
HOME02	0.1396 (3.0030)**	0.1517 (2.6449)**
EDUCMOTH	0.0659 (1.5037)	0.0688 (1.2822)
FORBORN	0.0015 (0.0370)	-0.0187 (-0.3777)
LIVEBOTH	0.0237 (0.5948)	0.0445 (0.9561)
EDUCFATH	-0.0109 (-0.2008)	0.0048 (0.0740)
BIRTHORDER	-0.0559 (-1.1375)	-0.0780 (-1.3365)
BIRTHWT	0.0140 (0.2216)	0.0381 (0.4899)
ASTHMA	-0.0190 (-0.5276)	-0.0505 (-1.3476)
CONSTANT	0.4617 (3.8214)**	0.4016 (2.7226)**

Asymptotic *t*-statistics in parentheses are computed using the corrected standard errors.

* $p < 0.1$

** $p < 0.05$

coefficients are functions of the first-stage coefficients, they too must be adjusted upward. The asymptotic formulas of Murphy and Topel (1985) were applied to make this adjustment.

Among the bias-corrected estimates in Tables 2 and 3, coefficients emerging as significant at the 0.05 level of a two-tailed test include PIATREAD, BPI, PUBSC, PRIVSC, T1, T2, and HOME02. Presence of a child's learning disability, LEARNDIS, is significant at the 0.1 level. Comparison of columns 1 and 2 in Tables 2 and 3 indicates that bias correction has a sizable upward impact on some of the estimated coefficients, particularly PUBSC and PRIVSC, for which we had weak instruments. However, with the exception of API (which we discuss further below), all of the statistically significant coefficients have *a priori* correct signs, and many have magnitudes meeting or exceeding estimates from prior studies.⁸ The discussion that follows is in reference to our bias-corrected estimates.

Turning first to PIATREAD and BPI, the estimated inverse relationship reported here runs counter to results in the literature (e.g., Farrington 1987; Werner 1989), which associate low academic achievement scores with an increased frequency of various social and behavior problems.⁹ However, our result occurs because we estimate a frontier directional distance function. Thus to obtain more of one good child outcome (*ceteris paribus*), the household must either sacrifice some amount of another good outcome, or it must tolerate more of a bad

⁸ Given that air pollution tends to be higher in metropolitan areas, API might well be serving as a proxy for residence in these areas. Results in Tables 2 and 3 have very low sensitivity to instrument combinations. Also, as a referee suggests, time-invariant covariates like HOME02 and BIRTHWT might plausibly be correlated with unobserved heterogeneity among sample households such as prenatal care and smoking and structural health hazards in the home. Nevertheless, our reported estimates proved to be insensitive to instrumenting HOME02 and BIRTHWT.

⁹ Though studies like these deal with multiple outcomes, they regress one outcome on another and on a set of explanatory variables. Thus that outcome selected to be the dependent variable has an asymmetric role relative to other outcomes. This asymmetry can affect the estimated parameters. With the multiple output directional distance function, we estimate jointly all inputs and outputs. A simple ordinary least squares regression (without instruments) of the levels of PIATMATH on all the other variables in the model indicates a significant positive relationship between PIATMATH and PIATREAD and a significant negative relationship between PIATMATH and BPI, which is consistent with this literature.

outcome. This is the fundamental nature of production at the frontier. An improvement in one skill score, holding constant BPI and all inputs, can be obtained only with a reduction in the other skill score. Further, an increase in either skill score, holding the other score and all inputs constant, can be obtained only with a concurrent increase in a bad.¹⁰

Public or private/religious school attendance tends to raise (lower) children's PIATREAD (BPI) scores by approximately the same magnitude when sample school participation rates are accounted for. In general, our estimates predict the average sample child's elementary school attendance to yield about a one standard deviation improvement (0.35 standard deviation decrease) in PIATREAD (BPI) over his or her 6–14 year-old age span.

Our results suggest a weak advantage in BPI reduction for children who attend public school; however, this difference is not statistically significant. We combine private and religious school attendance into one category. This left us with only seven remaining families/children who represent neither PUBSC or PRIVSC attendance (less than 2% of our sample). Of these seven children, two confirm a disability, one reports home schooling, and one reports no schooling. Given that these seven children live in seemingly diverse circumstances (e.g., other health problems, remote residence, or parent in the military) not common to the bulk of our sample children, a larger sample may alter our results.

From Table 3, our estimates indicate that a child's baseline home score exerts a strong positive (negative) impact on reading aptitude (behavioral problems). Like Todd and Wolpin (2006), the coefficient associated with HOME02 is positive and highly significant; however, we find the marginal impact of HOME02 on child verbal aptitude to be an order of magnitude greater than that found by Todd and Wolpin. For example, we find a 1% increase in HOME02 to raise the average child's PIATREAD reading score by about 0.85%. A 1% increase in HOME02 is also predicted to reduce the average child's BPI score by about 1.7%. We believe this difference to be due mainly to our estimation of a multioutput transformation function. Our estimates also exceed those reported by Blau (1999), who concludes (using like cohorts of the NLSY79-CS) that the impact of a higher HOME score on child aptitude scores is not trivial but not large either. He estimates that a one standard deviation increase in HOME raises mean PIATREAD scores by less than half our estimate. Our estimates suggest that the quality of a child's home environment at an early age, at least as measured by the HOME inventory, has a substantial impact on the set of child outcomes defined in terms of fundamental reading and verbal skills and behavioral sociability observed at later stages in the child's life.¹¹

We find no other time-varying or time-invariant variables to be significant at the 0.05 level. In the latter category are variables such as race, sex, and mother's background. Within either category, the most important determinants of good outcomes are home quality, school attendance, and the maturation of the child.¹²

¹⁰ Note, however, that it is possible for families to simultaneously increase goods and decrease bads if they lie inside the frontier.

¹¹ In other regressions not reported, we included both measures of HOME for ages 0–2 and 3–5. While the HOME02 coefficient remained virtually identical in magnitude to its stand-alone estimate, the HOME 3–5 coefficient, albeit positive, was small in magnitude and highly insignificant. We attribute this result mainly to the fact that the 0–2 and 3–5 HOME scores are highly positively correlated.

¹² The lack of significance of BIRTHWT in our second-stage estimates may be due in part to a higher than normal proportion of children in our sample who were "high birth weight" (greater than 141 ounces), and relatively few children who were "very low" birth weight (less than 52 ounces). About 20.25% of our sample was high birth weight. Though this proportion is close to the NLSY79-CS general sample proportion of 19%, it is higher than the national average of 15.5% (Hedley et al. 2004).

Table 4. Household Inefficiency \tilde{u}_{it}^F in Child Outcome Production

Interview Wave	Mean	Standard Deviation
1996	1.840	0.657
1998	1.50	0.594
2000	1.453	0.630

If one is willing to draw inferences from estimates with somewhat less than conventional statistical precision, Tables 2 and 3 present some other results worthy of mention. The signs of API and ASTHMA appear to suggest an indirect effect of air pollution on children's reading and behavior outcomes via a positive impact on children's respiratory problems; API-enhanced child respiratory problems, in turn, exert a negative impact on PIATREAD and a positive impact on BPI. Also, the coefficient for MOMWKHRS suggests that labor supply of working mothers has a positive (negative) impact on children's PIATREAD (BPI). Although our result is clearly not precisely estimated, the magnitude of our estimate closely resembles the Blau and Grossberg (1992) finding of a four-to-five-point positive effect of maternal labor force participation on cognitive ability test scores of NLSY79-CS children ages three to four (as of the 1986 survey wave). Blau and Grossberg offer two explanations for this positive effect: first, that nonmaternal care during this period of a child's life, which typically involves broader contacts with other children and adults, may exert a positive effect on early cognitive development; and second, that the indirect effect of an increase in family income due to the mother's employment plays an increasingly dominant role, thus producing an overall positive maternal labor supply effect as children reach preschool age.¹³

With stochastic frontier models, interest often centers upon differences in relative productivities over time. Table 4 presents by interview wave the fitted distance, \tilde{u}_{it}^F in standardized units, of the average sample household away from the "best practice" frontier. For 1996 the average measure of inefficiency is 1.84 standard deviations. In 1998 this average measure decreases to 1.5 and then to 1.45 in 2000. This temporal pattern is consistent with parental learning by doing in household production and/or greater child receptivity to parenting. Although efficiency improvement continues over the 6–14-year-old age span of our sample children, it slows considerably as children progress from age 10 and into their early teenage years. Because \tilde{u}_{it}^F is additive, the implication from Equation 3 is that the average household child with PIATREAD score of 33.82 could have produced a score approximately 23 points higher in 1996 and approximately 20 points higher in each of 1998 and 2000. At the same time, the bad outcome (BPI) could have been reduced to near zero in all years.¹⁴ In sum, Table 4 results suggest that households' inefficiency can vary widely and that the marginal improvement in inefficiency appears greatest for younger children. The substantial movements toward the frontier that occur simply with the passage of time and maturation of the child are greater than those due to increased inputs such as home environmental quality, family income, and parent and grandparent attributes.

¹³ Note, however, that our distance function suggests a potential negative indirect latent effect of MOMWKHRS on PIATREAD via the negative marginal impact of MOMWKHRS on HOME02.

¹⁴ This illustrates the directional properties of the distance function. Also, a zero BPI score is not atypical. A number of parents in our sample report a zero or near zero BPI for their child.

5. Conclusions

This paper employs a new methodology to model the impact of multiple inputs upon multiple measures of child outcomes. We estimate an output-oriented stochastic directional distance function with multiple inputs and outputs, embodying bad as well as good child inputs and outcomes. This allows us to compute partial effects of time-varying as well as time-invariant variables, while measuring the technical efficiency of households over time. For a balanced panel of 369 households with 6-to-14 year-old children in 1996, 1998, and 2000, we compute a two-step estimator. In the first stage we use instrumental variables to compute the within-estimator, test for the validity of the instrument set, correct for weak-instrument biases, and compute partial effects of good and bad inputs on reading, mathematics, and behavioral attributes. In the second stage we recover the effects of time-invariant variables on these measures and adjust their estimated standard errors.

Our estimates indicate that school attendance, a better home environment, and the passage of time significantly help children's cognitive development and reduce their behavioral problems. Other time-invariant characteristics, such as race, sex, and birth order, are insignificant. At the margin, the positive impacts of school attendance, home environment, and particularly time itself exceed the contributions of all other observed time-varying and time-invariant household inputs as well as child, parent, and community characteristics. The indirect effects of input interactions may be as important to child outcomes as are the direct effects of individual inputs. For example, our estimates suggest a negative, indirect pathway of poor air quality upon children's cognitive and behavioral outcomes through its positive impact on children's respiratory problems.

We provide evidence that some households are more effective technically than others at producing child outcomes, especially at the margin for children in the earlier part of their first decade of life. Our results differ sufficiently from much of the received wisdom about the household production of child health to suggest the importance of accounting for jointness among child outcomes and the relative inefficiencies of different households in producing these outcomes. Although the magnitude of the average sample household's technical inefficiency is not immodest, there may other reasons for inefficient household performance. Households may also fail to achieve allocative efficiency, representing ineffective responses to relative prices, lack of access to markets, or resource scarcities in household decision making. They may also fail to adapt in a timely fashion to changes in these prices or scarcities. Examination of these issues is a subject for future research.

If there is a single policy implication of this research it is the following: It is critically important to engage children in a quality home and school environment over time. Interventions that provide parents better access to and understanding of the technology of child health production and that encourage family members to remain committed to each other will have substantial societal payoffs.

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