The Evolution of Cognitive and Noncognitive Skills Over the Life Cycle of the Child

Flavio Cunha and James J. Heckman
University of Chicago

2007 AEA Conference
Friday, January 5, 2007, 10:15 AM
Session: The Interrelationship Between Cognitive and Noncognitive Skills
Presiding: Gary Becker

Introduction

- The importance of cognitive skills in explaining socioeconomic success is now firmly established (see Herrnstein and Murray, 1994; Murnane, Willett and Levy, 1995; Cawley, Heckman and Vytlacil, 2001).
- An emerging body of empirical research documents the importance of noncognitive skills for wages, schooling and participation in risky behaviors (See Bowles, Gintis, and Osborne, 2001; Borghans et al., 2006; Heckman, Stixrud, and Urzua, 2006, and Urzua, 2006).

- Heckman, Stixrud, and Urzua (2006) demonstrate that cognitive and noncognitive skills are equally important in explaining a variety of aspects of social and economic life, and not just wages, in the sense that movements from the bottom to the top of the noncognitive and cognitive distributions have comparable effects on many outcome measures.
- There is work on the determinants of the evolution of cognitive skills (Todd and Wolpin, 2003).
- There has been little work on the determinants of the evolution of noncognitive skills.

- Building on the theoretical analysis of Cunha and Heckman (2007) and Cunha, Heckman, Lochner, and Masterov (2006), we analyze the joint evolution of cognitive and noncognitive skills over the life cycle of the child.
- We model the self productivity of skills as well as their dynamic complementarity.
- Our technology formalizes the notion that noncognitive skills foster acquisition of cognitive skills by making children more adventuresome and open to learning.
- It also formalizes the notion that cognitive skills promote the formation of noncognitive skills.

- With our estimated technology, it is possible to define and measure critical and sensitive periods in the life cycle of child development, and to determine at which ages parental and other inputs most affect the evolution of different skills.
- Child development psychologists have long advocated the importance of understanding the formation of noncognitive skills for interpreting the effects of early childhood intervention programs (see Raver and Ziegler, 1997).
- Heckman, Stixrud, and Urzua (2006) note that the Perry Preschool program did not raise IQ but promoted success among its participants in a variety of aspects of social and economic life.

- Our analysis of noncognitive skills, their role in shaping cognitive skills, our investigation of the role of cognitive skills in shaping noncognitive skills, and our determination of the effectiveness of parental inputs on the formation of both types of skill over the life cycle, is a first step toward providing a unified treatment of the early intervention and family influence literatures.

- The conventional approach to the estimation of cognitive production functions, best exemplified by the research of Todd and Wolpin (2003, 2005), is to estimate a production function for cognitive test scores relating inputs to outputs.

- A central problem is accounting for the endogeneity of inputs.

- Another problem is the wealth of candidate parental input measures available in the Children of NLSY (CNLSY) data that we use that Todd and Wolpin (2005) analyze, and that we utilize in this paper.
- The confluence of these two problems–endogeneity and the multiplicity of input measures–places great demands on standard instrumental variable (*IV*) and fixed effect procedures, such as those used by Todd and Wolpin.
- It is common in studies of cognitive production functions for analysts to have more inputs than instruments.
- It is standard in the literature on the evolution of cognitive skills to use arbitrarily constructed indices of inputs to circumvent this problem and reduce the parental input data to more manageable dimensions.

- Fixed effects methods widely used in the cognitive production function literature invoke strong assumptions about separability of the technology of skill formation in observables and unobservables, and the way unobservables enter the model.
- Our approach to the identification of the technology of skill formation bypasses these problems.
- We estimate a dynamic factor model that exploits cross equation restrictions (covariance restrictions in linear systems) to secure identification using a version of dynamic state space models (Watson and Engle, 1983; Shumway and Stoffer, 1982).

- The idea underlying our approach is that cognitive and noncognitive skills are low dimensional latent variables.
- So are parental investments.

- Building on the analysis of Jöreskog and Goldberger (1975), Jöreskog, Sörbom, and Magidson (1979), Bollen (1989) and Carneiro, Hansen, and Heckman (2003), we use a variety of measurements related to skills and investments to proxy latent skills and investments.
- With enough measurements relative to the number of latent skills and investments, we can identify the latent state space dynamics generating the evolution of skills through cross-equation restrictions.
- We economize on the instruments required to secure identification, which are often scarce.
- When instruments are required, they are internally justified by our model.

- We solve the problem of the multiplicity of measures of parental investments by using all of them as proxies for low dimensional latent investments.
- Instead of creating an arbitrary index of parental inputs, we estimate an index that best predicts latent skill dynamics.

- We also address a recurrent problem in the literature on cognitive production functions and apply it to both cognitive and noncognitive test scores.
- Studies in this tradition typically use a test score as a measure of output (see, e.g., Hanushek, 2003), and do "value added" analysis on test scores.
- Yet test scores are arbitrarily normalized.
- Any monotonic transformation of a test score is also a valid test score.
- Value added—the change in test scores over stages (or grades)—is not invariant to monotonic transformations.
- This has become fashionable in recent NCLB studies.

- We solve the problem of defining a scale for output by anchoring our test scores using the adult earnings of the child, which have a well defined cardinal scale.
- We use other anchors such as high school graduation, college enrollment and the like.
- We set the scale of the latent factors that generate test scores by determining how the latent factors predict earnings.
- It matters empirically.

- Applying our methodology to CNLSY data we find that:
- (1) Both cognitive and noncognitive skills change over the life cycle of the child.
- (2) Parental inputs affect the formation of both noncognitive skills and cognitive skills, but with different impacts at different stages of the child's lifecycle.
- Direct measures of mother's ability affect cognitive skills but not noncognitive skills.
- (3) We find evidence for sensitive periods for parental inputs in the acquisition of cognitive skills and noncognitive skills.

- The sensitive periods for cognitive skills occur earlier in the life cycle of the child than do sensitive periods for noncognitive skills.
- Another way to say the same thing is that parental inputs appear to affect cognitive skill formation more strongly at earlier ages.
- They affect noncognitive skill formation more strongly at later ages.
- This finding is consistent with the evidence presented in Carneiro and Heckman (2003) that noncognitive skills are more malleable at later ages than cognitive skills.
- (4) Noncognitive skills affect the accumulation of cognitive skills (across self-productivity); reverse effect is weaker.

A Model of Cognitive and Noncognitive Skill Formation

- Becker and Tomes (1979, 1986) assume one period of childhood.
- Cunha, Heckman, Lochner, and Masterov (2006) and Cunha and Heckman (2007) analyze multiperiod models of childhood. Today, for simplicity we talk in terms of a model where there are two periods of childhood, "1 " and "2". Our estimates are for multiple period technologies.
- There are two kinds of skill: θ^C and θ^N.
- θ^C is cognitive skill and θ^N is noncognitive skill.

- I_t^k is parental investments in child skill k in period t, $k = C, N$ and $t = 1, 2$.
- h is the level of human capital as the child starts adulthood which depends on both θ_2^C and θ_2^N. The parents fully control the investment in the child.
- Each agent is born with initial conditions $\theta_0 = \left(\theta_0^C, \theta_0^N\right)$.
- Family environmental and genetic factors may influence these initial conditions (see Olds, 2002, and Levitt, 2003).
- At each stage t let $\theta_t = \left(\theta_t^C, \theta_t^N\right)$ denote the vector of skill or ability stocks.

- The technology of production of skill k in period t is:

$$\theta_t^k = f_t^k\left(\theta_{t-1}, I_t^k\right) \tag{1}$$

for $k = C, N$ and $t = 1, 2$.

- Assume standard neoclassical properties.
- In this model, stocks of both skills and abilities produce next period skills and influence the productivity of investments.
- Consistent with both critical and sensitive periods where inputs are more productive.

- Adult human capital h is a combination of different period 2 skills:

$$h = g\left(\theta_2^C, \theta_2^N\right). \tag{2}$$

- This specification of human capital assumes that there is no comparative advantage in the labor market or in other areas of social performance.

- This is relaxed in our other papers.

- We make this intergenerationally consistent by embedding it into a Laitner OLG model. Today we analyze one generation.

Identifying the Technology using Dynamic Factor Models: A Log Linear Technology

- Todd and Wolpin (2005) use a scalar measure of cognitive ability (θ_{t+1}^{C}) in period $t+1$ that depends on period t cognitive ability (θ_{t}^{C}) and investment (I_t).
- They assume a linear-in-parameters technology

$$\theta_{t+t}^{C} = a_t\theta_{t}^{C} + b_t I_t + \eta_t \tag{3}$$

- η_t represents unobserved inputs, measurement error, or both.
- They work only with test scores; we
  - (a) Work with test scores and test scores anchored in adult outcome measures
  - (b) Analyze both cognitive and noncognitive test scores
  - (c) Do not rely on IV/fixed effects methods, but exploit covariance restrictions.

Estimating the Technology of Production of Cognitive and Noncognitive Skills

- (1) We analyze the evolution of both cognitive and noncognitive outcomes using the equation system

$$\begin{pmatrix} \theta_{t+1}^{N} \\ \theta_{t+1}^{C} \end{pmatrix} = A_t \begin{pmatrix} \theta_{t}^{N} \\ \theta_{t}^{C} \end{pmatrix} + B_t I_t + \begin{pmatrix} \eta_{t}^{N} \\ \eta_{t}^{C} \end{pmatrix} \tag{4}$$

- I_t can be a vector and B_t a suitably dimensioned coefficient matrix.

- (2) We determine how stocks of cognitive and noncognitive skills at date t affect the stocks at date $t+1$, examining both self productivity (the effects of θ_t^N on θ_{t+1}^N, and θ_t^C on θ_{t+1}^C) and cross productivity (the effects of θ_t^C on θ_{t+1}^N and the effects of θ_t^N on θ_{t+1}^C) at each stage of the life cycle.
- (3) We develop a dynamic factor model where we proxy $\theta_t = \left(\theta_t^N, \theta_t^C\right)$ by vectors of measurements on skills which can include test scores as well as outcome measures.

- In our analysis, test scores and parental inputs are indicators of the latent skills and latent investments. We account for measurement errors in output and input measures. We find substantial measurement errors in the proxies for parental investment.
- (4) Instead of imposing a particular index of parental input based on components of the home score, we estimate indices of input.

- (5) Instead of relying solely on IV and exclusion restrictions to generate instruments to correct for measurement error in the proxies for θ_t and I_t, and for endogeneity, we use covariance restrictions that exploit the feature of our data that we have many more measurements on θ_{t+1}, θ_t and I_t than the number of unobserved factors.
- This allows us to secure identification from cross equation restrictions using *MIMIC* (Jöreskog and Goldberger, 1975) and *LISREL* (Jöreskog, Sörbom, and Magidson, 1979) models.

- We assume access to measurement systems for θ^k_{t+1}, θ^k_t, I_t and assume that we can represent the measurements by a dynamic factor structure:

$$\begin{aligned} Y^k_{j,t+1} &= \mu^k_{j,t+1} + \alpha^k_{j,t+1}\theta^k_{t+1} + \varepsilon^k_{j,t+1}, \quad j = 1, \ldots, m^k_{t+1}, \\ Y^k_{j,t} &= \mu^k_{j,t} + \alpha^k_{j,t}\theta^k_t + \varepsilon^k_{j,t}, \quad j = 1, \ldots, m^k_t, \qquad (5) \\ X_{\ell,t} &= \mu^X_{\ell,t} + \beta_{\ell,t} I_t + \varepsilon^I_{\ell,t}, \quad \ell = 1, \ldots, m^I_t, t = 1, \ldots, T, \\ & k = C, N \qquad (6) \end{aligned}$$

- Components of the ε's are mutually independent, and all pairs are independent of θ^k_{t+1}, θ^k_t, I_t.
- M_k are mother's characteristics (her education, etc.).

$$M_{k,t} = \mu^M + \alpha_M A + \varepsilon^A_{k,t}, \quad k = C, N$$

- Allow the components of $(\theta_{t+1}, \theta_t, I_t)$ to be freely correlated for any t and with any vector $(\theta_{t'+1}, \theta_{t'}, I_{t'})$, $t' \neq t$, and we can identify this dependence.

We Prove Semiparametric Identification for the Model

- Recover the joint distributions of $\left\{\theta_t^C, \theta_t^N\right\}_{t=1}^T$, A, $\left\{I_t\right\}_{t=1}^T$, $\left\{\eta_t^k\right\}_{t=1,k=C,N}^T$, $\left\{\varepsilon_{j,t}^k\right\}_{j=1}^{m_t^k}$, $\left\{\varepsilon_{\ell,t}^I\right\}_{\ell=1}^{m_t^I}$ and $\left\{\varepsilon_{\ell,t}^A\right\}_{\ell=1}^{m_t^A}$ nonparametrically, as well as the parameters $\left\{\alpha_{j,t}^k\right\}_{j=1,t=1}^{m_t^k}$, $\left\{\beta_{j,t}\right\}_{j=2}^{m_t^I}$, $\left\{\gamma_{j,t}^k\right\}_{j=1}^5$for $k = C, N$.
- With enough measurements and a smaller number of factors, we can identify the model.

The Identification of the Technology Parameters

- Focus on the Law of motion for noncognitive skills:

$$\begin{aligned} \theta_{t+1}^N &= \gamma_{1,t}^N \theta_t^N + \gamma_{2,t}^N \theta_t^C + \gamma_{3,t}^N I_t \\ &\quad + \gamma_{4,t}^N S + \gamma_{5,t}^N A + \eta_t^N \end{aligned} \tag{7}$$

$$\text{for } t = 1, \ldots, T.$$

- Parallel analysis can be performed for cognitive skills.
- η_t^N is serially independent but possibly correlated with all of the latent factors.

- Substitute the measurement equations $Y^N_{1,t+1}, Y^N_{1,t}, Y^C_{1,t}, X_{1,t}$, and M, for $\theta^N_{t+1}, \theta^N_t, \theta^C_t, I_t$, and A respectively:

$$
\begin{aligned}
Y^N_{1,t+1} \;=\; & \gamma^N_{1,t} Y^N_{1,t} + \gamma^N_{2,t} Y^C_{1,t} + \gamma^N_{3,t} X_{1,t} \\
& + \gamma^N_{4,t} S + \gamma^N_{5,t} M_1 \\
& + \underbrace{\begin{pmatrix} \varepsilon^N_{1,t+1} - \gamma^N_{1,t}\varepsilon^N_{1,t} - \gamma^N_{2,t}\varepsilon^C_{1,t} \\ \\ -\gamma^N_{3,t}\varepsilon^I_{1,t} - \gamma^N_{5,t}\varepsilon^A_1 + \eta^N_{t+1} \end{pmatrix}}_{\omega^N_{t+1}} .
\end{aligned} \tag{8}
$$

- If we estimate (8) by least squares, we do not obtain consistent estimators of $\gamma^N_{k,t}$ for $k = 1, \ldots, 5$ because the regressors $Y^N_{1,t}$, $Y^C_{1,t}$, $X_{1,t}$, and M_1 are correlated with the error term ω_{t+1} where:

$$\omega^N_{t+1} = \varepsilon^N_{1,t+1} - \gamma^N_{1,t}\varepsilon^N_{1,t} - \gamma^N_{2,t}\varepsilon^C_{1,t} - \gamma^N_{3,t}\varepsilon^I_{1,t} - \gamma^N_{5,t}\varepsilon^A_1 + \eta^N_{t+1}.$$

- However, using Madansky (1964), can instrument $Y^N_{1,t}, Y^C_{1,t}, X_{1,t}$, and M_1 using $\left(Y^N_{j,t}\right)^{m^N_t}_{j=2}, \left(Y^C_{j,t}\right)^{m^C_t}_{j=2}, (X_{j,t})^{m^I_t}_{k=2}, (M_k)^{m_A}_{k=2}$.

- The $\left(Y_{j,t}^{N}\right)_{j=1}^{m_t^N}, \left(Y_{j,t}^{C}\right)_{j=2}^{m_t^C}$ are valid instruments as long as in equation (4) $A_t \neq (0)$, so the factors are correlated over time.
- The $(X_{j,t})_{k=2}^{m_t^I}$ are valid instruments for $X_{1,t}$ as a consequence optimal investment behavior.
- The $(M_\ell)_{\ell=2}^{m_A}$ are valid for M_1 because of the common factor generating them.
- Using two stage least squares with these instruments allows us to recover the parameters $\gamma_{k,t}^{N}$ for $k = 1, 2, 3, 4, 5$.
- Instruments are the internal instruments justified by the model.

Identification and Estimation of the Model
The data (CNLSY)

- Sample of the 1053 white males from the Children of the NLSY/79 (CNLSY/79) data set.
- The measures of quality of a child's home environment that are included in the CNLSY/79 survey are the components of the Home Observation Measurement of the Environment - Short Form (HOME-SF).
- A variety of measures of parental input.

- We have a set of both cognitive and noncognitive test scores from the NLSY/1979 for the Parents.
- The cognitive test scores are the ASVAB tests used to form AFQT (widely used in empirical economics).
- The noncognitive test scores are the Pearlin test scores (the Pearlin test scores are measures of self-esteem).

- We also have a set of both cognitive and noncognitive test scores from the CNLSY/1979 for the Children of the NLSY.
- The cognitive test scores are the PIAT tests (used by Todd and Wolpin).
- The noncognitive test scores are the Behavior Problem Indexes.
- We observe parental earnings (y_t).
- We observe different components of parental wealth (S_t).

- We observe the family demographics and characteristics such as:
    1. Age of the mother at the birth of the child
    2. Number of family members
    3. Residential Location: South vs. Nonsouth, Urban vs. rural.

Investments in Skills of the Children

We have the components of the HOME-SF. At each age *t* of the child:

- Number of Books
- Availability of musical instruments
- Availability of a daily newspaper
- Whether the child receives special lessons
- Frequency of trips to museums
- Frequency of trips to the theater
- Frequency with which the child sees the father

- Amount of time the child spends with the father indoors
- Amount of time the child spends with the father outdoors
- How often the child eats with the mother and father
- How often the child sees relatives
- We do not take these as the direct measurements, but as *proxies* for the measurements

Empirical Results

- Assume that parental preferences can be represented by a quadratic utility function, and the technology functions are linear in the state variables.
- In this case, the policy functions are also linear (e.g., Sargent, 1987).
- If we assume that the distribution of the uniquenesses ε_t, the error terms η_t, and the initial distribution of the factors are normal, we can estimate the model using the Kalman Filter.
- First consider a model with an autonomous (age-invariant) technology.

The Unanchored Technology Equations (using test scores alone)

	Next Period Noncognitive Skills		Next Period Cognitive Skills	
	Mean	Standard Error	Mean	Standard Error
Current Period Noncognitive Skills	0.8835	0.0215	0.0282	0.0131
Current Period Cognitive Skills	0.0181	0.0130	0.9814	0.0388
Current Period Investment	0.0601	0.0206	0.0566	0.0137
Mother's Education	0.0067	0.0088	0.0047	0.0062
Mother's Ability	-0.0063	0.0069	0.0290	0.0104
Variance of Shocks	0.1357	0.0219	0.0340	0.0091

- (1) Both cognitive and noncognitive skills show strong persistence over time;
- (2) noncognitive skills affect the accumulation of next period cognitive skills, but cognitive skills do not affect the accumulation of next period noncognitive skills;
- (3) the estimated parental investment factor affects noncognitive skills somewhat more strongly than cognitive skills, although the differences are not statistically significant;
- (4) the mother's ability affects the child's cognitive ability but not noncognitive ability;

- (5) the mother's education plays no role after controlling for parental investments. These results are robust to alternative normalizations of the factor loadings on the measurements associated with family inputs that set the scale of the parental investment factor as we discuss below.
- Dynamic factors are statistically dependent.

Contemporaneous Correlation Matrices

Period 1 - Children ages 6 and 7

	Noncognitive	Cognitive	Investment (Home)
Noncognitive	1.0000	0.2089	0.3217
Cognitive	0.2089	1.0000	0.2712
Investment (Home)	0.3217	0.2712	1.0000

Period 2 - Children ages 8 and 9

	Noncognitive	Cognitive	Investment (Home)
Noncognitive	1.0000	0.2406	0.3797
Cognitive	0.2406	1.0000	0.3478
Investment (Home)	0.3797	0.3478	1.0000

Contemporaneous Correlation Matrices

Period 3 - Children ages 10 and 11

	Noncognitive	Cognitive	Investment (Home)
Noncognitive	1.0000	0.2668	0.4500
Cognitive	0.2668	1.0000	0.4459
Investment (Home)	0.4500	0.4459	1.0000

Period 4 - Children ages 12 and 13

	Noncognitive	Cognitive	Investment (Home)
Noncognitive	1.0000	0.2868	0.5318
Cognitive	0.2868	1.0000	0.5714
Investment (Home)	0.5318	0.5714	1.0000

- Test score scales arbitrary.
- Anchoring matters.

The Technology Equations - Anchored in Adult Earnings of the Child Measurement Variables are Standardize with Mean Zero and Variance One

	Next Period Noncognitive Skills		Next Period Cognitive Skills	
	Mean	Standard Error	Mean	Standard Error
Current Period Noncognitive Skills	0.8835	0.0215	0.0790	0.0367
Current Period Cognitive Skills	0.0065	0.0046	0.9814	0.0388
Current Period Investment	0.0030	0.0010	0.0079	0.0019
Mother's Education	0.0003	0.0004	0.0007	0.0009
Mother's Ability	-0.0003	0.0003	0.0041	0.0015
Variance of Shocks	0.0003	0.0001	0.0007	0.0002

The Technology Equations - We anchor the parameters on the probability of graduating from High School

	Next Period Noncognitive Skills		Next Period Cognitive Skills	
	Mean	Standard Error	Mean	Standard Error
Current Period Noncognitive Skills	0.8848	0.0231	0.0745	0.0125
Current Period Cognitive Skills	0.0007	0.0365	0.9814	0.0250
Current Period Investment	0.0073	0.0031	0.0120	0.0043
Mother's Education	0.0004	0.0016	0.0022	0.0029
Mother's Ability	-0.0016	0.0119	0.0058	0.0167

- We estimate stage-specific technologies to test for critical and sensitive periods in cognitive and noncognitive skills.

The Technology Equations
Estimated Parameter Values - Technology from Period 1 to Period 2

	Next Period Noncognitive Skills		Next Period Cognitive Skills	
	Mean	Standard Error	Mean	Standard Error
Current Period Noncognitive Skills	0.9862	0.0141	0.0624	0.0242
Current Period Cognitive Skills	0.0508	0.0712	0.9235	0.0912
Current Period Investment	0.0462	0.0131	0.1170	0.0152
Mother's Education	0.0035	0.0032	-0.0080	0.0059
Mother's Ability	0.0074	0.0410	0.0567	0.0413
Variance of Shocks	0.1425	0.0141	0.0646	0.0152

The Technology Equations
Estimated Parameter Values - Technology from Period 2 to Period 3

	Next Period Noncognitive Skills		Next Period Cognitive Skills	
	Mean	Standard Error	Mean	Standard Error
Current Period Noncognitive Skills	0.9405	0.0132	0.0220	0.0072
Current Period Cognitive Skills	-0.0417	0.0814	0.8871	0.0213
Current Period Investment	0.1119	0.0173	0.0397	0.0131
Mother's Education	-0.0025	0.0079	0.0124	0.0083
Mother's Ability	-0.0048	0.0132	0.0067	0.0069
Variance of Shocks	0.1286	0.0152	0.0232	0.0064

The Technology Equations
Estimated Parameter Values - Technology from Period 3 to Period 4

	Next Period Noncognitive Skills		Next Period Cognitive Skills	
	Mean	Standard Error	Mean	Standard Error
Current Period Noncognitive Skills	0.7597	0.0351	0.0021	0.0041
Current Period Cognitive Skills	0.0511	0.0254	0.9124	0.0409
Current Period Investment	0.0375	0.0144	0.0294	0.0103
Mother's Education	0.0082	0.0125	0.0036	0.0041
Mother's Ability	-0.0073	0.0183	0.0193	0.0413
Variance of Shocks	0.1574	0.0172	0.0103	0.0029

Per Period Correlation Matrices
Technology Parameters are allowed to vary over time

Period 1 - Children ages 6 and 7

	Noncognitive	Cognitive	Investment (Home)
Noncognitive	1.0000	0.1822	0.3263
Cognitive	0.1822	1.0000	0.2704
Investment (Home)	0.3263	0.2704	1.0000

Period 2 - Children ages 8 and 9

	Noncognitive	Cognitive	Investment (Home)
Noncognitive	1.0000	0.2687	0.3698
Cognitive	0.2687	1.0000	0.3684
Investment (Home)	0.3698	0.3684	1.0000

Per Period Correlation Matrices
Technology Parameters are allowed to vary over time

Period 3 - Children ages 10 and 11

	Noncognitive	Cognitive	Investment (Home)
Noncognitive	1.0000	0.2832	0.4094
Cognitive	0.2832	1.0000	0.4279
Investment (Home)	0.4094	0.4279	1.0000

Period 4 - Children ages 12 and 13

	Noncognitive	Cognitive	Investment (Home)
Noncognitive	1.0000	0.2858	0.4647
Cognitive	0.2858	1.0000	0.5653
Investment (Home)	0.4647	0.5653	1.0000

- We can estimate the weights on the family inputs instead of using ad hoc weights.
- It matters.
- Consider an example for the first period of the child technology.

The Weights in the Construction of the Investment Factor Ages 6 and 7

	Estimated Weights[1]	Ad Hoc Weights[2]	Share of Total Residual Variance due to Factors[3]	Share of Total Residual Variance due to Uniqueness[4]
Number of Books	0.3079	0.1667	0.1242	0.8758
Musical Instrument	0.1997	0.1667	0.1417	0.8583
Newspaper	0.1932	0.1667	0.1517	0.8483
Child has special lessons	0.1431	0.1667	0.2808	0.7192
Child goes to museums	0.0740	0.1667	0.3063	0.6937
Child goes to theater	0.0821	0.1667	0.3068	0.6932

- We also find evidence for multiple investment factors.
- One investment factor is specialized to the father's inputs.
- The other to the mother's inputs.

Summary

- Cognitive and noncognitive skills evolve over the life cycle of the child. The correlation across these skills increases with age.
- Noncognitive skills foster the accumulation of cognitive skills.
- Family environments and investments causally affect both cognitive and noncognitive skills.
- Investments are more effective for cognitive skills in the early years.
- They are more effective in the later years for noncognitive skills.
- Strong evidence of self-productivity and cross self-productivity.

- We develop and apply a method for using a multiplicity of proxies for family inputs that
  (a) do not impose arbitrary scales on the measures as, e.g., in the home score,
  (b) allow us to estimate measurement error components.
- There is considerable measurement error in the proxies for latent skills and investments.
- We find evidence of multiple family input factors including one strongly associated with the father.
- Moving beyond test scores and anchoring test scores in adult outcome measures affects the analysis of cross productivity effects.