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Abstract

This paper estimates production functions of child cognitive and social development using a panel data of nine-year old children each with over two hundred home and school inputs as well as family background variables. A tree regression method is used to conduct estimation under various specifications. A small subset of inputs is found consistently important in explaining variances of child development results, including the number of books a child has at various ages and how often a mother reads to child by age five, while the effects of race and maternal employment are negligible when detailed inputs are controlled.

Key words: child development, tree regression method, panel data.

JEL: I20, J13, C40.

1 Introduction

An old Chinese saying claims that a person's lifetime achievements can be well predicted by his performance at age seven. Its validity in modern times is confirmed by recent evidence. In Britain, for example, a person's test scores at age seven are significantly associated with his education level and earnings in thirties (Currie and Thomas 2001). In the U.S., skill endowment heterogeneity at age sixteen may account for ninety percent of the total variance of individual lifetime earnings (Keane and Wolpin 1997). One possible reason for the vital importance of skill formation in early childhood is that "success or failure at this stage feeds into success or failure in school which in turn leads to success or failure in post-school learning" (Heckman 1999).

The main goal of this paper is to estimate production functions of early child cognitive and social development results. Since home and school inputs are often endogenous choices of parents and

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hence are correlated with each other and across periods, any omitted inputs would necessarily cause bias in estimated effects of included ones. To minimize the omitted variable problem, this paper adopts various within-child difference and value-added specifications to deal with the unobserved family and child fixed factors, and uses a comprehensive set of detailed inputs: Based on National Longitudinal Surveys 1979 Youth (NLSY79) data in the U.S., we construct a sample of 4726 eight- and nine-year-old children with over two hundred inputs from mother prenatal care until current period.[1]

Current scientific knowledge, however, does not tell us which inputs among the two hundred plus available ones in the data affect child development and how they may interact with each other. Furthermore, most inputs are measured by categorical variables with multiple items, and many contain missing values. Researchers faced with these problems are often forced to choose, quite arbitrarily, which variables to include in and what structures to impose on production functions, how to combine different categories, and how to handle missing variables. Important information may be lost during this subjective data reduction process (Harvey 1999), and different treatments per se may give rise to discrepant estimation results even for the same data (Haveman and Wolfe 1995). This motivates us to adopt a non-parametric method, namely tree structured regression, in estimation. The optimization mechanism underlying the tree regression is similar to the conventional linear regression; its non-parametric features are designed to select important explanation variables, detect non-linear structures, and treat missing values in a systematic way (Breiman, Friedman, Olshen, and Stone 1984).[2]

The estimation results in various specifications yield a consistent picture, where a reasonably small set of earlier and current inputs are important predictors for child development results at age eight or nine. The number of books a child has at various ages and how often a mother reads to her child before age 5 are the most important predictors of child math and reading scores from age five onwards; they are also primary predictors of child behavior problem scores at age 5. Spanking a child aged 8-9 seems to be mostly driven by family or child fixed factors and have no effects on current result, while spanking a younger child may reduce his future behavior problems. When

[1] Even with this rich data set, one may still worry about omitted variable problems. To check this, we include in the regressions many family background variables, which should be correlated with omitted inputs. Since they never show up as primary explaining predictors, it suggests that the influence of omitted variables, if any, is very modest.

[2] This is the first time regression tree analysis is used extensively in child development area, though it has been applied in medical, biological, weather forecasting and many other areas. In economics and finance literature, it was used occasionally to detect regime shifting patterns (e.g. Durlauf and Johnson, 1995).

detailed home and school inputs are controlled, a mother's working hours in the first five years of a child's life have little effects child development results at age 8-9; so does a child's race or sex.

There is a large body of literature studying the contributing factors to child cognitive and social-emotional development. A lot of work examines the effects of maternal employment on early child development results (Blau and Grossberg 1992, Parcel and Menahan 1994, Harvey 1999, Ruhm 2000, Waldfogel et al. 2002, Baum 2003). Most of these studies use linear regression models taking control of various family background variables. Their findings are mixed and no consensus has been reached, probably due to ad hoc selection of control variables and omitted variable problems mentioned above (Haveman and Wolfe 1995, Todd and Wolpin 2003). The current paper find no effects of mother working on child development once detailed inputs are included. This is consistent with the finding of Waldfogel et al. (2002) that the effects of maternal employment are much reduced after a couple of home quality indicators are controlled. A possible explanation is that a mother's quality time with children is not much affected by her labor force participation (Bianchi 2000).

Another strand of literature examines the role of child care (e.g. NICHD ECCRN 2001, 2003). The overall quality of child care is found to be modestly related to child development outcomes, while family factors are more consistent predictors. This finding is also confirmed by our estimation results where the type of child care, the duration and intensity of child care experiences in the first three years never show up as primary explaining variables.

The paper shows that the racial gaps of math and reading scores among eight and nine year-old children can be completely accounted for by home and school inputs. This is a striking result since a substantial Black-White test score gap persists even after controlling for a wide range of characteristics (Fryer and Levitt 2004, Todd and Wolpin 2004).

The school inputs in general have less explanation power than home inputs. This is consistent with the finding of Parcel and Durfur (2001) that the effects of school inputs on child behavior are modest in size, while home inputs are stronger. Similarly, the standard school inputs such as class size, pupil-teacher ratio, and teacher experiences are usually found to have little effects on children attainment (Feinstein and Symons 1999).

The results also suggest that, though earlier scores are very important in predicting future results, they may not be sufficient statistics for historical inputs. Indeed, some earlier inputs have direct effects on current child performance beyond what is already captured by earlier scores. For example, the number of books a child has at age seven and how often his mother reads to him around age three are primary indicators of his math and reading scores at age nine, even when corresponding scores at age seven are controlled.

The paper is organized as follows. The childhood history sample is described in section 2. Regression tree analysis and various estimation methods are discussed in the subsequent two sections. The results of regression trees are presented in section 5. The final section concludes.

2 Data: Childhood History Samples

Starting from 1986, children born to mothers of National Longitudinal Surveys 1979 Youth (NLSY79) are surveyed every two years. The set of child development results and inputs from birth up to 10 years is different across three age-groups, namely 0-2 years, 3-5 years, and 6-9 years. We construct a sample of 4726 children each of whom has a single pair of comparable scores and inputs at ages 6-7 and 8-9, plus historical inputs at ages 0-5, mother prenatal care, mother working history up to the fifth year after child birth, and family backgrounds. For children five years old and above, the cognitive development is measured by PIAT (Peabody Individual Achievement Test) math and reading recognition scores, while social and behavioral development is measured by BPI (Behavior Problem Index) Total Scores.

A brief introduction of home and school inputs as well as maternal working and family backgrounds is in order. For children age three and above, home environment variables include how many books a child has, how often a mother reads to child, how often a father plays with him outdoors, whether there are music instruments and newspapers at home, whether parents encourage hobbies and bring a child to enriching activities, how often the family gets together with relatives and friends, how often a child watches TV and attends religious service etc. For younger children, home inputs also include the number of various toys a child has, how often he is talked to and taken to grocery shopping, whether he was breast-fed and how long the breast-feeding last, whether a mother teaches a child letters, numbers, and shapes, etc. The child care experiences in a child's first three years are measured by whether a child is in regular child care, the type of child care, the months per year and hours per week in child care. Variables about parenting styles include how often a child is expected to make bed, to clean room, etc., and how mother responds to low grades, tantrums, and hits. Mother prenatal care variables include mother usage of alcohol, cigarettes, vitamins, and sonograms during pregnancy, and whether a child has low birth weight. Maternal employment history covers a mother's working hours one year before child birth up to the fifth year afterwards. Family backgrounds include a mother's highest grades, AFQT scores, age at child birth, her marital status, her wages, the salary income and total family incomes, the region the family lives, whether the mother ever lived in the south in her youth, whether there is a father figure at home, whether he is the biological father, etc. The school inputs include school types, number of hours a child working on homework, mother's rating of school quality including teacher skill and caring of students, safety of school, moral teaching, etc.

3 Regression Tree Analysis

A regression tree is a piecewise linear estimate of a regression function constructed by recursively partitioning the data.[3] It is grown by sequentially splitting the sample into binary nodes/subsets. At each node, every explaining variable competes in its ability to reduce the node variance; the variable with the best improvement score is selected to be the *primary splitter.* Unlike the linear regression, here not all available predictors show up as primary splitters: The primary splitters must be the best predictive variable at some node. The tree growing process continues until the variances in all nodes are less than some threshold. The tree is then pruned backwards to get a sequence of trees with different number of terminal nodes; the pruning rule balances the trade-off between the out-of-sample resubstitution errors and the complexity of the trees. From this whole sequence the *optimal tree* is selected using test sample or cross-validation error estimate.[4] The *importance* of a variable measures its overall ability as a primary splitter in an optimal tree to explain the variance of dependent variable in all nodes; it corresponds to the variable's total effect on the dependent variable.

Overall, the accuracy of regression tree has been generally competitive with linear regression. It can be much more accurate on nonlinear problems, though it tends to be somewhat less accurate on problems with good linear structure; this is not a problem here since most variables are categorical. A main drawback of the tree regression, determined by its non-parametric characteristics, is that it

[3] There are various ways in conducting tree regressions. The one used here, also the mostly widely used, is CART (Classification And Regression Tree) established by Breiman et al. (1984). The tree regression can be conducted in a similar manner as implementing linear regressions using a standard statistical software.

[4] Take the test sample estimate as an example. A subset is selected randomly from the whole sample as the *learning sample* to grow the mother tree, while the remaining one is the independent *test sample.* Use each subtree on the test sample to predict the dependent variable and calculate the resulted sum of squared errors; the subtree with the minimum relative test error (compared to mean squared error) is selected as the optimal tree.

does not provide the traditional statistical significant tests. However, variables selected as primary splitters tend to be also significant in the conventional sense since they are the best predictive variables among many available ones and their predictive abilities are further tested on a random test sample.[5]

4 Estimation Methods

We run tree regressions according to various specifications used in the literature. The simplest estimation method uses only contemporaneous home and school inputs, labeled *current input regression*, which yields unbiased estimates when only current inputs matter and when they are unrelated to unobserved child ability. The *historical input regression* include both current and historical inputs; if some historical inputs act as primary splitters, then current input regressions are biased.

One way to allow for unobserved child ability is using an earlier score as its proxy. The *value-added historical regression* includes an earlier score in addition to current and historical inputs. If historical inputs act as primary splitters, it suggests they have direct effects on future child development and hence the earlier score is not a sufficient statistic for them.

Another way is to use *within-child difference regression,* where the regressant is the first difference in scores of the same child at different times, while regressors include both current and earlier inputs. This eliminates the effects of unobserved child ability and gets unbiased estimates when (1) child ability has the same effect on scores, (2) it does not interact with inputs in any non-linear way, and finally (3) input choices in the second period do not depend on the first period's random shock. The third condition can be explicitly checked since we have variables on how a mother responds to low grades and behavioral problems; it holds for cognitive development production functions but not so well for social and behavioral development. To further check the degree of endogeneity problem for disciplines, a regression is run using the behavior scores at age 7 as the dependent variable, while including future inputs at ages 8-9 as well as current and earlier inputs. Age 8-9 inputs would appear as primary splitters when the endogeneity problem is severe. But the opposite is true; actually the optimal regression tree does no change before and after including these future inputs. This evidence

[5] Though it is technically infeasible to replicate the tree analysis using linear regression for the current project, I do try to use the linear regression method by reducing the categorical variables to binary versions, ignoring any interactive terms, and omitting missing values. The main results are similar: the family background and child care variables are rarely significant, while the home inputs selected as primary explaining variables in the tree regressions are often significant in the OLS as well.

suggests the endogeneity problem is too weak to affect the main results.

5 Estimation Results

The main regression results are summarized in tables 1-3, where the importance levels of primary splitters for the included regression trees are listed.[6] Recall that an input's importance measures its total effect on the dependent variable.

5.1 Math Scores for Children at Ages 8-9

Table 1 summarizes regression results for PIAT math scores. In the current input regression 'Current', race is the most important predictor. When it is excluded in 'C/race', however, the relative error increases by only 0.02, while the effects of books and TV watching hours at weekdays are almost doubled, and the degree of physical affection shown by mother to child as well as several other home inputs become primary splitters. When earlier inputs are included in 'History', the importance of race is halved compared with 'Current'. When race is excluded in 'H/race', many inputs become primary splitters including special activities and TV watching hours at weekdays, while the importance of existing primary splitters has little change. These results suggest that most effects of race on math scores can be accounted for by earlier and current inputs a child receives, though race is a good proxy for detailed home inputs when they are not available.

Comparing the two columns 'C/race' and 'H/race', it is clear that earlier inputs are important to PIAT math scores. In general, the importance of current inputs goes down in the historical input tree, which suggests that their estimated effects in current input tree are biased upward. For example, the importance of books at ages 8-9 is greatly reduced (from 15.3 to 1.29) while the number of books at ages 6-7 becomes the most important predictor.

In the value-added historical regression 'VAY' where PIAT math score at age 7 is used, earlier inputs such as books at ages 6-7 and mother reading to child at ages 3-5 still have positive effects, though their importance is reduced. This implies that the previous PIAT math score, though with very high importance, is not a sufficient statistic for earlier inputs. The only current input selected is a mother's physical affection for child.

The extreme importance of the math score at age 7 in predicting the score two years later may suggest that child ability has large effects on math scores. But how does child ability in math evolve

[6] Detailed regression trees are available upon request.

over time? To shed some light on this question, the math score at age 5 is used as a proxy for child ability in 'VAB'. The three primary splitters are the number of books at ages 6-7 and 8-9, and special activities at ages 8-9. The importance of math score at age 5 is much lower than that at age 7, while the total importance of inputs increases. One implication is that a child's ability in math is affected by home inputs especially books and enriching activities. The explaining power of inputs alone, however, is quite low since no optimal within-child tree exists for the math score.

Among all inputs, the number of books a child has at ages 6-7 and 8-9, mother's physical affection for child, special activities, and mother reading to child at ages 3-5 appear as primary splitters in at least one of the three value-added regressions.

5.2 Reading Scores for Children at Ages 8-9

Table 2 summarizes six regression trees for PIAT reading scores. For both current and historical input trees, regressions with and without race are strikingly similar. When historical inputs are included in column 'History', books at ages 6-7 becomes the most important input (with importance 18.7) and the importance of books at ages 8-9 is greatly reduced (from 19.8 to 3.52), which is exactly the same scenario as in the math score regressions. In the value-added historical tree 'VAY' with reading score at ages 6-7, the top two inputs are books at age 7 and child reading habit at ages 8-9. This implies that the earlier reading score is not a sufficient statistic for earlier inputs. In 'VAB' with ages 5 reading score, the aggregate importance of inputs is higher, which suggests the reading ability is also affected by home inputs. In within-child regression, the most important inputs are the number of books and child reading habit at ages 8-9.

Overall, the number of books and a child's reading habit at ages 8-9 are the most important inputs predicting a child's reading scores at ages 8-9. The important inputs and their ranking are quite similar in both reading and math score regressions; a difference is that reading scores are affected by more inputs in value-added and within-child specifications.

5.3 Behavior Problem Scores for Children at Ages 8-9

Table 3 summarizes five BPI regression trees. The difference between current and historical input trees is quite small; the only earlier input that matters is spanking frequency at ages 6-7, while the importance levels of spanking and grounding a child at ages 8-9 do not change. In the value-added historical tree 'VAY' using the BPI score at age 7, the frequencies of grounding and sending a child to room are still primary splitters, though the importance of grounding is much reduced; in contrast, the large effect of spanking at ages 8-9 disappears. Since no earlier inputs show up, the age 7 BPI score seems to be a sufficient statistic for both ability and earlier inputs.

When the BPI score at age 5 is used in 'VAB', the number of grounding and room-sending at ages 8-9 are still the most important inputs. Many other inputs also become primary splitters including some inputs at ages 3-5, so BPI score at age five is not a sufficient statistic for earlier inputs. The relative error in 'VAB' is only 0.015 points higher than 'VAY', which suggests the difference between BPI scores at ages 5 and 7 can be mostly accounted for by home inputs. The within-child tree using age 5 BPI score is presented in the last column, where spanking a child at ages 3-5 is negatively (though modestly) associated with his behavior problem at ages 8-9, while the opposite is true for sending a child to room at ages 8-9. The errors are very high, and no within-child tree exists using ages 7 BPI score.

In these behavior problem regressions, the number of times sending a child to room, grounding him, and how often he reads for self-enjoyment at ages 8-9 are selected as primary splitters in most specifications even when an earlier score is controlled. In sharp contrast, though the current spanking frequency is the most important predictor in both current and historical input trees, it never appears in any value-added or within-child difference specifications. This suggests spanking a child of ages 8-9 merely reflects some family- or child-specific fixed factors. Spanking a child at ages 3-5, however, is negatively associated with his behavior problem at ages 8-9 as shown in the within-child regression.

5.4 Child Development Results at Age 5

A common feature of the various regressions above is that child development results at age 5 are very important for future outcomes. So it is interesting to know how the age 5 results are affected by home inputs. The results are briefly described below, though the detailed table is omitted. The number of books and how often a mother reads to child at ages 3-5 are important for both cognitive and social development, while the latter is the most important input for math and reading scores; the spanking frequency at ages 3-5 is the best predictor of BPI scores at age 5. Race matters only for math score, and again its effect is partially accounted for by books, reading to child, and birth order.

Overall, books and how often a mother reads to her child appear to matter most for child cognitive development at age 5; they are also the primary predictors for behavior problems at age 5, though spanking is most predictive. The errors are generally higher than corresponding regressions of child development results at ages 8-9.

6 Conclusion

Early child development is a crucial part of human capital formation. The paper estimates production functions of child cognitive and social development at ages 8-9 using NLSY(79) child data, where over two hundred home and school inputs starting from mother prenatal care periods are included as well as many family background variables. A tree structured regression method is used to conduct estimation, and the unobserved family or child heterogeneity is handled by within-child difference and value-added specifications. The omitted variable problem is greatly mitigated by using a very rich set of detailed inputs and further checked by including family backgrounds in the regressions. The endogeneity problem of disciplinary inputs is checked by putting future inputs at ages 8-9 into the regressions of child development results at age 7. The evidence shows that the influence of this problem, if any, is very weak.

Detailed home inputs are found to be the most important predictors of child development results. Production functions of child math and reading scores are more similar to each other than to behavior problem scores. The number of books a child has at various ages, how often a child reads for self-enjoyment, and how often a mother reads to her child before age 5 are among the most important inputs predicting math and reading scores from age 5 onwards. A child's behavior problem score at ages 8-9 is mostly correlated with parental disciplining such as how often he gets grounded or sent to room, while the score at age 5 is also affected by how often his mother read to him and the number of books he had. Spanking a child aged 8-9 has no effects on current results, while spanking a younger child may reduce his future behavior problems.

A reasonably small set of inputs from over two hundred available in the data are selected as primary predictors for child cognitive and social development results at age eight and nine, which may be used as a rough guide for variable selection in relevant research. Though there is some evidence suggesting the estimated effects of these home and school inputs are more than correlations, future research is needed to further establish the causal links.

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Table 1: Effects of Home and School Inputs on PIAT Math Scores at Age 8-9

Inputs	Current	C/race	History	H/race	VAY	VAB
Current inputs at age 8-9						
# of books a child has	6.04	15.3	1.29	1.29		2.53
# of hours/weekday child sees TV	3.07	6.07		2.82		
# showing child physical affection	3.12		0.75	1.02		
how often child reads for enjoyment	2.39	2.62	2.79	2.48		
child gets special help w/remedial work	3.42	1.98		1.10		
# past week mom spanked child	1.46	1.24	1.66			
child gets special lessons/activities	1.39			4.46		2.74
Mom keeps closer eye if low grades		1.09	0.96			
Mom responds to tantrum-time out	1.48					
Mom responds to tantrum-talk with child	1.24	1.23				
parents participate with school	1.22					
Earlier inputs						
# of books a child has at age 6-7	--	--	17.4	17.4	1.40	2.14
teacher caring of child at age 6-7	--	--		1.26		
# of books a child has at age 3-5	--	--	1.91	1.45		
Mom helps child learn shapes at age 3-5	--	--	1.71	1.91		
child has record/tape player at age 3-5	--	--	1.27			
how often mother reads to child at age 3-5	--	--	1.05		0.59	
race (White versus Black/Hispanic)	15.95	--	7.72	--		
Earlier Scores						
PIAT math score at age 7	--	--	--	--	67.7	--
PIAT math score at age 5	--	--	--	--	--	39.8
Sample Variance	190	190	190	190	190	194
Sum of Squared Errors on test sample	0.83	0.85	0.844	0.838	0.65	0.79
Sample Size	2992	2992	2992	2992	2992	2008

Notes: The entries are the importance levels of inputs, which measures its total effect on the dependent variable. Current -- Only current inputs at age 8-9 included; C/race if race excluded. History -- Historical inputs included; H/race if race excluded. VAY -- Value-added regression with age 7 score and all inputs. VAB -- Value-added regression with age 5 score and all Inputs. Some inputs with importance less than one are not listed in the table. In the `C/race' they are: how often mom reads to child, how often child eats w/ parents, is there music instrument at home, and # times mom says positive things in past week. In the `H/race' they are: how often child taken to performance, whether child gets special assignment for advanced work, limits non-school activity if low grades, # mom grounded child in past week, how often child is expected to bathe self, child ever sees father-figure at age 6-7, birth order, # child reads for enjoyment at age 6-7, mom responds to hit-send to room at age 3-5, hours mom worked/week 4th quarter and 5th year after child birth, and how often child eats with parents by age 2.

Table 2: Effects of Home and School Inputs on PIAT Reading Scores of at Age 8-9

Inputs	Current	C/race	History	VAY	Within	VAB
Current inputs at age 8-9						
# of books a child has	19.8	19.8	3.52		2.99	3.18
how often child reads for enjoyment	8.9	8.9	9.28	2.51	2.37	
child gets special help w/remedial work	10.3	10.3	10.7			3.97
how often child eats with parents	1.67	1.67				0.6
#times past week mom spanked child	1.60	1.60		1.59		
parents participate with school	1.40					
child gets special lessons/activities	1.21	2.40				
how often child w/ dad outdoors					1.01	
Mom rating of teacher caring					0.92	
Mom punishes child for low grades					0.68	
school communicates with parents		1.15				
# hours/weekend day child sees TV		1.08				
how often child expected to clean room						1.34
Earlier inputs						
# of books a child has at age 6-7	--		18.7	3.57		3.91
# past week child spanked at age 6-7	--				1.66	
# mom shows child affection at age 6-7	--				0.68	
# child reads for enjoyment at age 6-7	--					1.95
# past week child grounded at age 6-7	--					1.59
child has record/tape player at age 3-5	--		2.7			
mom's attitude on child learning by age 3	--		1.55			
how often mother reads to child by age 3	--				0.70	
race (White vs. Black/Hispanic)	2.68	--	2.13		0.96	
Earlier scores						
PIAT reading score at age 7	--	--	--	97.8	--	--
PIAT reading score at age 5	--	--	--	--	--	55
Sample Variance	221	221	221	221	120	224
Sum of Squared Errors on test sample	0.825	0.827	0.835	0.57	0.966	0.74
Sample Size	2982	2982	2982	2982	2982	1935

Notes: The entries are the importance levels of inputs, which measures its total effect on the dependent variable. Current -- Only current inputs at age 8-9 included; C/race if race excluded. History -- Historical inputs included; H/race if race excluded. VAY -- Value-added regression with age 7 score and all inputs. VAB -- Value-added regression with age 5 score and all Inputs. Within -- Within-child regression using age 7 score and all inputs.

Table 3: Effects of Home and School Inputs on BPI Total Scores at Age 8-9

Input	Current	History	VAY	VAB	Within
Current inputs at age 8-9					
#times past week mom spanked child	19.6	19.6			
#times past week mom grounded child	9.9	9.9	3.11	8.24	
#times past week mom sent child to room	4.65	4.0	3.98	4.14	3.92
how often child reads for enjoyment	3.93	1.84		1.09	1.53
how often family gets with relatives and friends	2.45				
how often child picks up after self				1.27	
Mom sees if child improves on own for low grades				0.92	
#times past week mom said positive things				0.61	
Earlier inputs					
#times past week mom spanked child at age 6-7	--	4.49		1.67	
#times past week mom took away TV at age 6-7	--				1.81
how often child w/ dad outdoors at age 6-7	--			1.35	
#times past week mom spanked child at age 3-5	--				1.31
Mom responds to hit--send to room at age 3-5	--			1.05	
Mom helps child learn alphabets at age 3-5	--			0.96	
Earlier scores					
BPI total score at age 7	--	--	79.6	--	--
BPI total score at age 5	--	--	--	51	--
Sample Variance	221	221	221	221	195
Sum of Squared Errors on test sample	0.87	0.86	0.68	0.69	0.98
Sample Size	3021	3021	3021	3021	2512

Notes: The entries are the importance levels of inputs, which measures its total effect on the dependent variable. Current -- Only current inputs at age 8-9 included. History -- Historical inputs included. VAY -- Value-added regression with age 7 score and all inputs. VAB -- Value-added regression with age 5 score and all Inputs. Within -- Within-child regression using age 5 score and all inputs.