How the Allocation of Children's Time Affects Cognitive and Noncognitive Development

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The allocation of children's time among different activities may be important for cognitive and noncognitive development. Here, we exploit time use diaries from the Longitudinal Study of Australian Children to study the effects of time allocation. By doing so, we characterize the trade-off between different activities to which a child is exposed. On the one hand, our results suggest that time spent in educational activities, particularly with parents, is the most productive input for cognitive skill development. On the other hand, noncognitive skills appear insensitive to alternative time allocations. Instead, they are greatly affected by the mother's parenting style.

I. Introduction

In the last decade a number of studies have found that skills measured at early ages (e.g., ages 3–6) are strong predictors of later life outcomes such

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as educational attainment, wages, employment, and choice of occupation as well as adolescent risky behaviors such as teenage pregnancy, criminal activity, smoking, and alcohol use. The factors found to predict later outcomes include both cognitive and noncognitive skills (e.g., perseverance, motivation, risk aversion, self-esteem). Examples of these findings can be found in the work by Keane and Wolpin (1997), Cameron and Heckman (1998, 2001), Cunha, Heckman, and Lochner (2006), Heckman, Stixrud, and Urzua (2006), and Bernal and Keane (2010, 2011).

Given the growing evidence of the importance of early childhood skills for later life outcomes—particularly economic outcomes—there has been a growing interest in investigating the determinants of these skills. Many studies have focused on how early childhood activities, as well as other influences like household income, school quality, child care, and so on, affect the development of skills or abilities.

However, the current literature is confronted with two main problems. First is the difficulty of measuring all of a child's activities, not to mention the many other inputs to child development. Second is the empirical problem of distinguishing a mere correlation between activities and skills from a true causal effect. To illustrate this, let us define the production function for skill Y of individual i observed at age a as

$$Y_{ia} = X'_{i\{K\times a\}}\theta_{\{K\times a\}} + \gamma_a\mu_i + \varepsilon_{ia}, \tag{1}$$

where X is the matrix of K inputs from age a backwards (the complete history of inputs), μ_i is the innate ability/personality of the child (at age 0), and ε is a transitory error term that captures shocks to the child development path. The inputs in X can be time inputs, such as time in school or with parents; goods inputs, such as number of books, intake of calories; and measures of the quality of these inputs, such as, for example, parental education or teacher-student ratios.

The first problem, measurement of a child's activities, originates from the fact that most surveys include only a limited amount of information about what a child does, where, and with whom. As a result, researchers have tended to focus on the effect of just a few of the many inputs into child development, and to group child time into very broad categories, such as time spent with the mother versus time spent in child care. This is problematic, however, because the estimated effect of any input depends on what other inputs are omitted in the equation.

To clarify this point, consider a simple world where a child's time T can only be allocated between child care T_C, time with parents T_P, and time watching television alone T_V, so that $T_C + T_P + T_V = T$. For simplicity, consider the special case where time not in child care is equally shared between time with parents and time watching television, so that $T_P = T_V = (T - T_C)/2$. Finally, let these three time inputs, and a latent ability endowment μ (likely correlated with the time inputs), be all that matter in the development of skill Y, so that the production function is simply $Y_i = \beta_0 + \beta_C T_{iC} + \beta_P T_{iP} + \beta_V T_{iV} + \gamma\mu_i + \varepsilon_i$, where ε_i is orthogonal to all other variables. A researcher who has imperfect knowledge of this simple world but who is interested in the effect of child care on skill Y might estimate $Y_i = \gamma_0 + \gamma_C T_{iC} + u_i$. Suppose the researcher is able to find a consistent estimator for γ_C such that $p\lim_{N\to\infty} \hat{\gamma}_C = \gamma_C$, and finds that $\hat{\gamma}_C > 0$. It is tempting to conclude that child care is good for the child. Yet it is easy to show that in our simple world $\gamma_C = \beta_C - [(\beta_P + \beta_V)/2]$. Thus γ_C is a relative effect. Whether or not child care is beneficial to the child depends on what substitutes for child care.[1]

For instance, let $\beta_C = 2$, $\beta_P = 3$, and $\beta_V = 0$. As a result $\gamma_C = 0.5 > 0$. But spending time in child care increases Y only if child care substitutes for time watching television (since $\beta_C > \beta_V$). In contrast, child care lowers Y if it substitutes for time with parents (since $\beta_C < \beta_P$). This simple world could be generalized to several activities and to goods inputs, where, given a financial constraint, parents substitute one good for another. In any case, the estimated coefficient of the observed input captures an effect relative to that of the unobserved/omitted inputs that act as substitutes. Thus, when a researcher studies the effect of a few inputs in isolation what we learn might be quite limited or misleading, even if the estimator is consistent.

Our aim is to estimate child (cognitive + noncognitive) skill production functions with an exceptionally rich set of time and other inputs. To do so we exploit diary data contained in the Longitudinal Study of Australian Children (LSAC), a survey following a cohort of children born in 1999 and surveyed biannually since 2004. The LSAC includes 24-hour diaries where parents provide information about *what* the child is doing, *where*, and *with whom*. It also contains very rich data on other inputs to child development.

In the first component of this paper we analyze the diary data to get a better view of how Australian children spend their time during a typical week. This has a value in itself because there are not many studies documenting children's time use. In the second and main component of our research we link the diary data to cognitive and noncognitive measures of ability, demographics, and parental background information. These additional data are provided in the LSAC main survey. We then investigate whether alternative time allocations lead to different levels of cognitive and noncognitive development: for example, time with parents versus other adult relatives, time in educational versus other activities, time with other children versus time using media, and so forth. Thus, our production function can be expressed as follows:

[1] More generally, let α be the share of time not in child care that is spent with the parents. Then $T_P = \alpha(T - T_C)$ and $T_V = (1 - \alpha)(T - T_C)$. It follows that $\gamma_C = \beta_C - \alpha\beta_P - (1 - \alpha)\beta_V$.

$$Y_{ia} = TI'_{i\{K\times a\}}\beta_{\{K\times a\}} + PB'_{i\{G\times a\}}\delta_{\{G\times a\}} + e_{ia}, \tag{2}$$

where TI is a matrix of K time inputs measured from age a backwards while PB is a matrix of G parental background characteristics (that proxy for both goods inputs and innate ability μ_i) and parenting style measures. The error term, e, includes omitted variables, measurement error, and shocks to the child development path. We construct the K time inputs such that $\sum_{k=1}^{K} TI_{ia\{k\}} = 168$, the number of hours in a full week.

By explicitly modeling the complete weekly time allocation we are able to rank time inputs according to their productivity: a ranking of the $\beta_{\{a\}}$ vector is informative about how a reallocation of a child's time from "unproductive" (bottom ranked) to "productive" (top ranked) time inputs at age a can enhance skill development. In other words, we characterize the trade-off between all alternative activities, home and school, to which a child is exposed. To our knowledge, this research is the first to estimate the effect of alternative overall time allocations on children's development—as opposed to examining effects of only one or two time inputs in isolation.

As we will see, from an econometric point of view the paper that is closest to ours is Todd and Wolpin (2007). However, their work differs from ours in that they do not attempt to estimate the effects of a range of alternative time allocations and other inputs. Instead, they proxy for a wide range of inputs into child development using the home environment index (HOME) in the US National Longitudinal Survey of Youth. All home inputs are proxied by this scalar index, obtained by adding up responses to a battery of questions about the home environment. In addition, school inputs are proxied by state- and county-level information on pupil-teacher ratios.

We believe that there are three important ways in which our work goes beyond Todd and Wolpin (2007). First, our measures of child inputs are more extensive. Note that the HOME index still fails to measure many important home inputs, such as the amount of time the child spends in activities with mothers and other caregivers, the amount of time spent watching TV or playing video games, and so on. Second, our input measures are more concrete. For instance, it is not at all clear what levers a parent or a policy maker would have to pull to move the HOME index. But time in child care, length of the school day, and so on can be altered in obvious ways. Third, we are able to characterize the trade-off between alternative home inputs (e.g., TV time vs. parent's time), which one cannot do using one scalar HOME input.

The second problem faced by the literature, distinguishing a mere correlation between activities and skills from a true causal effect, is also severe. In equation (1) endogeneity can come in three forms: (1) omitted variables, since we do not observe μ or some of the other inputs in X; (2) simultaneity, if Y causes X and not vice versa (e.g., does reading books make children smarter or do smart children read more books?); (3) measurement error in

X, for example, it is legitimate to ask whether the parent knows exactly (or truthfully reports) how many hours the child spent reading.

The literature has proposed different estimation strategies to deal with these problems. The papers by Todd and Wolpin (2003, 2007) specify a production function where a test score is a function of home and school inputs together with unobserved initial ability. They then discuss a set of nonnested estimators and the assumptions under which each of these estimators identifies the production function. The set of estimators include ordinary least squares (OLS), fixed effects (within family and within child), and value added, among others. They attempt to address the identification problem by comparing results from these different statistical models. Since they have no strong prior on what model best deals with endogeneity, Todd and Wolpin (2007) pick the model that minimizes the out-of-sample root mean-squared error (RMSE). They then focus on inferences from the preferred model.

Our objective is rather different. That is, we will eschew any attempt to choose a "best" model, as any criterion we could use would necessarily be controversial.[2] Rather, our goal is to determine whether there exists a ranking of inputs that is robust across the whole range of the most popular models used in the literature (e.g., value added, fixed effects, etc.). As each estimation method attempts to handle endogeneity in a different way, relying on different maintained assumptions, we would have more confidence in a ranking of inputs that is robust across methods. A robust ranking of the time inputs, if it exists, implies that a reallocation of time use can enhance child development.[3]

The simple example we presented earlier shows that analyzing one input in isolation conveys only partial and potentially misleading information because we cannot characterize the trade-off between inputs. We have argued that this makes it important to try to measure all of a child's activities. Clearly, having multiple endogenous inputs makes the estimation problem much more difficult. If our model contained just one endogenous input, then an instrumental variable or equally suitable quasi-natural experiment

[2] For instance, the RMSE criterion used by Todd and Wolpin (2007) chooses the "best" model based on fit, but the best-fitting model does not necessarily deal with the endogeneity issues.

[3] The papers by Cunha and Heckman (2007, 2008) propose a different approach in order to investigate the self-productivity and dynamic complementarities between cognitive and noncognitive skills. They use a system of equations where future cognitive and noncognitive skills are simultaneously determined by their current level (self and cross), a measure of the current parental investment and unobserved inputs. Identification in their system relies on cross-equation covariance restrictions. We do not replicate Cunha and Heckman (2007, 2008) strategy inasmuch as it is not our aim to uncover self-productivity and dynamic complementarities between cognitive and noncognitive skills. Moreover, we are interested in the effect of several (K) alternative time inputs rather than a one-dimensional investment factor.

approach might be possible. But estimating the β vector in equation (2) by instrumental variables (IV) requires $K - 1$ exclusion restrictions (as the β on one time input is normalized to 0 for identification). Finding such a large set of valid instruments is not feasible in our application. Therefore, we feel that in rich models like ours it is more practical to deal with endogeneity using other approaches (e.g., fixed effects, value added models) combined with sensitivity analysis.[4]

Our results suggest that time spent in educational activities, particularly with parents, is the most productive input for cognitive skills. A reallocation of children's time that favors these kinds of activities by substituting away from less productive ones would have a positive effect on cognitive skill. This result is robust to different identification assumptions. Perhaps surprisingly, we also find that, for reading skills, media time does not appear to be any worse than other noneducational time uses, like time in before/after school care. However, noncognitive skills like behavioral problems, social skills, and emotional problems appear insensitive to alternative time allocations. Instead, these skills greatly depend on some aspects of parenting style. A style that combines effective (but not harsh) discipline with parental warmth leads to the best noncognitive outcomes. This finding on parenting style is new in the economics literature.

II. Data

The Longitudinal Study of Australian Children (LSAC) is a biannual survey that began in 2004. The LSAC follows two cohorts of children: one born March 1999–February 2000 (4,983 children) and one born March 2003–February 2004 (5,107 children). These are known as the "K cohort" and the "B cohort." Both cohorts have been surveyed three times, in 2004, 2006, and 2008 (a fourth survey is currently in the field). Table 1 illustrates the average age at interview for each cohort/wave pair.

For both cohorts the survey collected a rich set of information about the children's skills, demographics, and parental background. In addition, the LSAC collected time use diaries, where parents recorded their children's activities over 24 hours. As far as we are aware, the only other data set combining information on children's skills/background with time use diaries is the US Child Development Supplement (CDS), a sample of children from households in the Panel Study for Income Dynamics. The CDS included time use diaries in 1997 (0–12-year-old children), in 2002 (5–18-

[4] We do not mean to say that IV would necessarily be the preferred approach if it were feasible. On the contrary, even if IV were feasible, it would merely provide another alternative method of dealing with endogeneity whose advantages/disadvantages would have to be compared to the other approaches we employ. Like them, IV is not assumption free. The *Journal of Economic Perspectives*, vol. 24, no. 2 (2010), has an excellent discussion on this topic. The point we are trying to make is that an IV approach is hardly an option in our context.

Table 1
Average Age at Interview

	Wave 1	Wave 2	Wave 3
K cohort	4 years and 9 months	6 years and 10 months	8 years and 10 months
B cohort	9 months	2 years and 10 months	4 years and 10 months

year-olds), and in 2007 (10–19-year-olds). Compared to the CDS, LSAC has the advantage of focusing on only two cohorts with a larger sample size. LSAC children are generally much younger than those in the CDS, who were born between 1984 and 1997. LSAC children are also surveyed biannually in contrast to the 5-year gap between the two waves of the CDS. This makes the LSAC an excellent data set to analyze early childhood development.

In the rest of the paper we limit our attention to the K cohort. The data for the younger B cohort lack consistent measures of skill because of changes in the type of test across waves. This prevents us from using some estimators like value added and fixed effects.

A. Time Use Diaries

The time use diary (TUD) collects details of the activities of the study children in LSAC over two 24-hour periods: one a specified weekday and one a specified weekend day. After the LSAC personal interview, the respondents were left with some self-complete forms, including the time use diaries. The interviewer worked through an example of how to complete the diary with the respondent, and the respondent was advised of the dates for which they should complete the diary. These dates were selected by the interviewer to ensure a random allocation of weekdays and a random allocation of weekend days. The diaries divided the 24-hour day into 96 15-minute intervals.[5]

For each child the diaries classified separately the activity (26 alternatives), where the activity took place (5), and with whom (7). Most diaries were completed by the child's mother (approximately 91%), with 7% completed by the child's father. The remaining 2% were completed by other family or carers. This is stable across waves.

[5] Parents were given specific dates to fill the diary, such as Tuesday, July 26, for the weekday diary and Saturday, July 30, for the weekend diary. They were also asked if they could not complete the diary on their allocated date to wait another week before completing it, such that the completion day was on the same day of the week as was the date selected for them. The objective was to have an even distribution among the 5 weekday days and between the 2 weekend days. We assume that the activity recorded in each time period lasted for the full 15 minutes. This may result in an overestimation of time spent in specific activities, when those activities take less than 15 minutes.

1. Original and Recoded Time Use

Figure A1 in the appendix, available in the online version of *Journal of Labor Economics*, gives an example of the diary and its coding. This is the example that parents were shown. The diaries did not change between waves 2 and 3. The diary at wave 1 (see fig. A2) is slightly different to account for age-specific activities.

If we divide the day into activities, where they took place, and whom they were with, we would obtain $26 \times 5 \times 7 = 910$ different time use categories. With our sample size it is not feasible to estimate how 910 types of time use affect child development. Thus, our first goal is to recode the data into a smaller set of categories. We choose to have nine mutually exclusive time use categories in order to facilitate the analysis while at the same time not losing valuable information. From our investigation of the data, we feel that a manageable list of activities is (time in):

1. Bed (*bed*),
2. School/day care (*sch*),
3. Educational activities with parents (*ped*),
4. Educational activities with adults other than parents (*oed*),
5. General care with parents (*pcr*),
6. General care with adults other than parents (*ocr*),
7. Social activities (*soc*),
8. Media (*mda*),
9. Not sure what child was doing (*unk*).

Note that we attempt to distinguish activities that have an educational component from those that involve basic child care, supervision, or child rearing. Educational activities include time spent reading a story, being talked to, or helping with chores. In contrast, general care includes activities such as traveling (transportation), being fed, or being cuddled. We further split these two categories depending on whether they are done with the parents or with other adults. In the appendix we fully describe our recoding algorithm.

Note that children could be coded to a number of activities concurrently, so the sum of time spent in different activities may exceed 24 hours. Unfortunately, parents were not asked to differentiate between the main activity being undertaken (primary activity) and any activities being undertaken concurrently (secondary activities). Thus, whenever the parent indicated that the child was in two or more concurrent activities within the same time slot, we assign the slot to what we consider the primary activity. The numbering 1–9 of the time inputs listed above reflects our ordering into primary, secondary, and so on. Say, for instance, a child was being fed by the mother (5, general care with parents) while also watching TV (8, media). We would code this as general care with parents since we consider this the primary activity. Also, note that we distinguish between cases where the activity was coded "Not sure what child was doing," an entry in the diary, and cases where the activity is simply missing (which are excluded).

2. *Attrition, Missing Data, and Sample Selection*

To simplify the discussion of problems with attrition, missing data, and sample selection we use forward slashes to indicate wave 1, wave 2, and wave 3 diary data (wave1/wave2/wave3). In the LSAC there are a total of 6,959/6,453/5,573 diaries for 3,728/3,385/2,906 children. Therefore, diary data are not available for 25% of the original sample of 4,983 children at wave 1. There is additional attrition of 7% between waves 1 and 2 and 10% between waves 2 and 3. Attrition in the main survey is 10% between waves 1 and 2, but only 3% between waves 2 and 3. Diaries were left to parents to complete and send back to LSAC administrators, while the main survey was collected with the interviewer present.

Among those parents who filled out a diary, not all returned both weekend and weekday diaries. Since our objective is to investigate time allocation during a week, we exclude these cases. Also, parents were asked to indicate whether the diary was completed on an ordinary day, a holiday, a crisis day, and so on. Since we would like the diaries to be as representative as possible of the child's typical time allocation, we exclude diaries filled out on nonordinary days. We further restrict our sample to diaries filled out within the school term dates.

Also, there are several diaries where not all of the 96 15-minutes slots were assigned to an activity. We choose to keep only complete diaries and do not impute unassigned slots with one exception: slots between 10 p.m. and 6 a.m. that are missing or coded "Not sure what child was doing" are recoded as time in bed sleeping.

Finally, we also drop cases with clear inconsistencies between the main and the diary data. An example is a parent indicating that the child is enrolled in school while the weekday diary data shows very low school time, or vice versa.

Table 2 shows the combined effects of attrition, missing data, and our other sample screens. Clearly the combined effect on sample size is sub-

Table 2
Diaries Completed

	Wave 1		Wave 2		Wave 3	
	Number	%	Number	%	Number	%
Main data	4,983	100.0	4,464	90.0	4,331	87.0
Time use diaries	3,728	74.8	3,381	67.8	2,905	58.2
1 weekend and 1 weekday diary	3,149	63.1	2,984	59.9	2,665	53.5
Our sample	1,314	26.4	1,064	21.3	591	11.8

NOTE.—Percentages are computed as a proportion of the original sample of 4,983 children.

stantial, as we have usable diaries for 26%, 21%, and 12% of the original sample by waves 1, 2, and 3, respectively. Still, we have sample sizes of over 1,000 in waves 1 and 2.

We next investigate whether attrition, missing data, and our screening criteria lead to sample selection with respect to the original sample. To do so we run a probit model where the dependent variable is equal to one if the child is in our sample and zero otherwise. The independent variables are demographic characteristics reported in the main survey. Table 3 presents the results. There is evidence of statistically significant selection on some observables. But the very small coefficients and pseudo-R^2 values suggest that selection on observables is quantitatively weak. For instance, children in our sample tend to have slightly better educated parents.

3. *Children's Time Allocation*

In this section we describe children's time allocation in our sample using the recoded activities as described above.

In figures 1, 2, and 3, we show the distribution of each time use category over a 24-hour period (tempogram). We present separate subfigures for the three waves. We use solid lines to describe weekday patterns and dashed lines to describe weekend patterns. The vertical axis measures the fraction of children in a specific category, while the horizontal axis shows the time of the day. Note that the vertical axes are not on a common scale across all panels. This makes it easier to see how each time input varies over the 24 hours but makes it harder to get a sense of how frequent each category is relative to the others. Not surprisingly, School/day care activities (*sch*) are most frequent between hours 9 and 16. After hour 18 almost no child is in preschool/day care. Educational activities with parents (*ped*) are widespread throughout the day, but with a mode in the evening (i.e., around hours 19–20). General parental care (*pcr*) is instead multimodal with peaks in the early morning, lunchtime, and evening. Both these patterns are intuitive given patterns of meals and bedtime reading, lending face validity to

Table 3
Differences between Original and Selected Samples

	Wave 1	Wave 2	Wave 3
Gender	−.029**	.003	.013
Child's age	−.000	−.004**	−.000
Number of siblings	−.008	−.018**	−.013**
Mother's income	−.003	.003	−.003
Father's income	.005**	−.000	.000
Max{M Ed, F Ed}	.014**	.007**	.006**
Pseudo R^2	.020	.010	.009

NOTE.—Max{M Ed, F Ed} = max years of education between mother and father. Numbers in table are marginal effects calculated at the means, except for gender (calculated for girls).
** Significant at the 5% level.

the diary data. Social activities (*soc*) are quite widespread throughout day, with higher frequency in the 8–9 and 15–18 time windows. Time using media (*mda*) peaks in the early morning and evening. Bed time has the expected U shape. Because of our coding algorithm there are no children in the "Not sure" (*unk*) category between 22 and 6 on the following day.

Table 4 shows the weekly distribution of time across children. Weekly hours are derived by multiplying the weekday allocation by 5 and the weekend day allocation by 2, and then by summing the two products. As expected there is more variation in school/child care time at wave 1 (when children are on average 4 years and 9 months old and are therefore attending child care/kindergarten/preschool) than at waves 2 and 3 (when children would be attending primary school). Since primary school hours are generally uniform across schools, the variation at waves 2 and 3 is mainly the result of before and after school care time. Time in school seems to reduce time with parents, both in educational or general care activities. It is also evident that both the level and standard deviation of educational and general care activities with other adults are much less than those with parents.

B. Children's Skills, Demographics, and Parental Background

1. Cognitive and Noncognitive Skills

The LSAC children were administered three cognitive skill tests depending on their age.

Peabody Picture Vocabulary Test (all waves): A short form of the Peabody Picture Vocabulary Test (PPVT-III), a test designed to measure a child's knowledge of the meaning of spoken words and his or her receptive vocabulary. Different versions of the PPVT containing different, although overlapping, sets of items of appropriate difficulty were used for children ages 4–5 years, 6–7 years, and 8–9 years. A PPVT stimulus book with 40 plates of display pictures was used. The child is not required to define words but to show what they mean by pointing to (or saying the number of) a picture that best represents the meaning of the word.

Matrix Reasoning Test (waves 2 and 3): Children completed the Matrix Reasoning Test (MRT) from the Wechsler Intelligence Scale for Children, 4th edition (WISC-IV) at ages 6–7 and 8–9 years. This test of nonverbal intelligence presents the child with an incomplete set of pictures (defined by geometric shapes) and requires them to select a picture that completes the set from five different options.

Who Am I? test (wave 1 only): The Who Am I? (WAI) is a direct child assessment measure that requires children to copy shapes and write numbers, letters, words, and sentences. It is used for the children at ages 4–5 to assess general cognitive abilities needed to begin school.

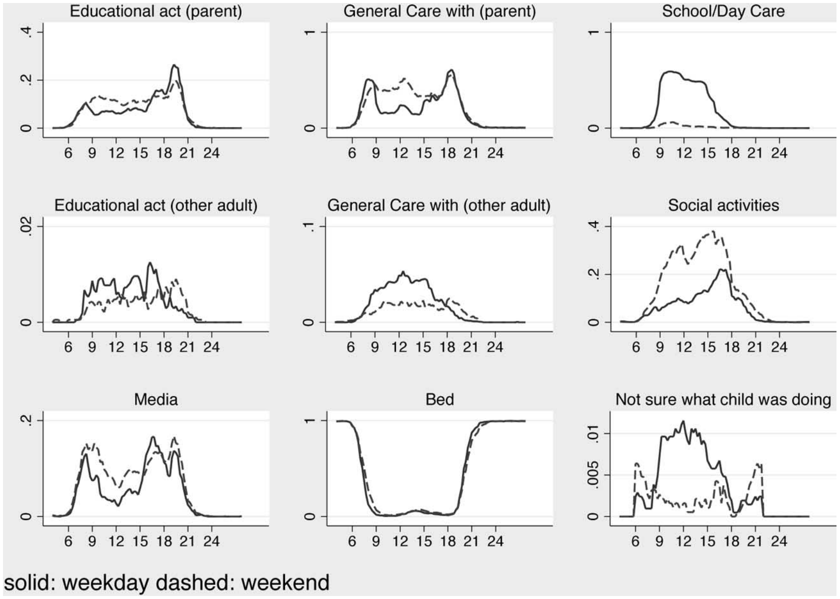

FIG. 1.—Tempogram, wave 1

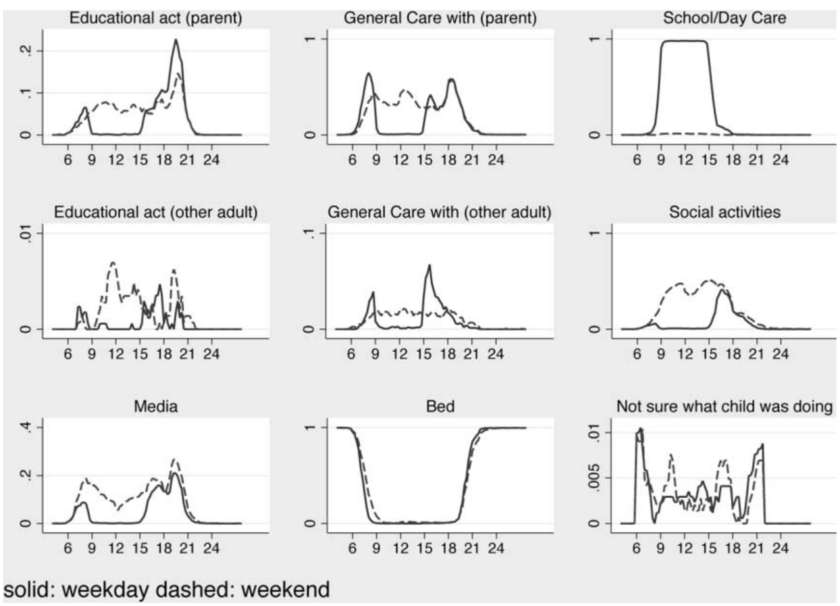

FIG. 2.—Tempogram, wave 2

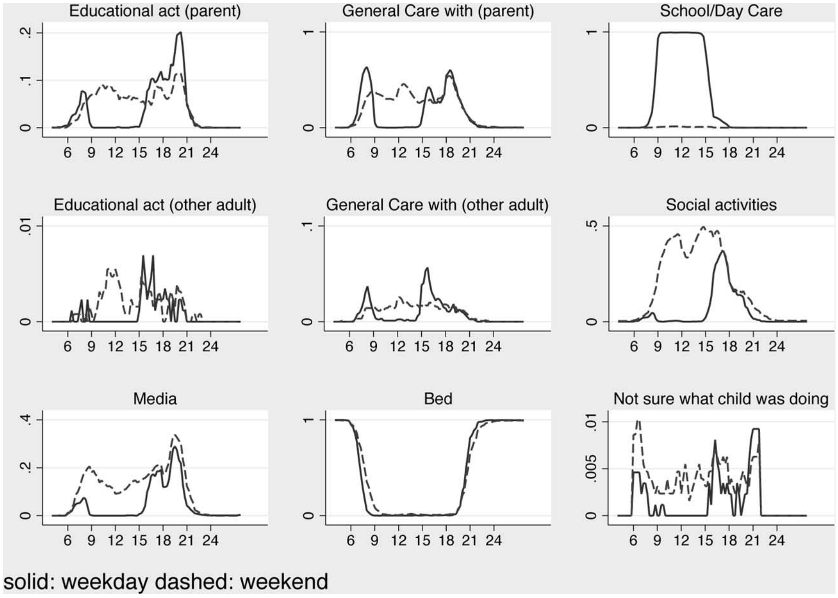

FIG. 3.—Tempogram, wave 3

Table 4
Weekly Time in Each Derived Activity

	Wave 1				Wave 2				Wave 3			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
ped	10.77	9.73	.00	82.50	5.82	3.90	.00	23.00	5.98	4.56	.00	26.50
pcr	31.15	11.18	.00	79.50	25.20	7.01	2.50	65.25	25.14	7.42	7.50	53.50
sch	19.85	16.04	.00	60.00	34.50	4.37	26.25	65.00	35.01	4.31	26.25	55.25
oed	.56	2.20	.00	25.00	.14	.78	.00	11.50	.15	.80	.00	12.00
ocr	2.62	6.83	.00	47.50	1.31	3.05	.00	29.25	1.34	3.25	.00	31.25
soc	14.10	9.43	.00	70.50	15.55	7.22	.00	51.50	14.49	7.14	.00	42.50
mda	9.17	6.87	.00	43.50	8.74	5.60	.00	32.25	10.49	6.80	.00	38.75
bed	79.35	6.84	40.25	139.75	76.43	5.34	40.75	92.75	75.19	5.52	47.00	92.25
unk	.43	3.05	.00	41.25	.30	1.48	.00	17.50	.21	1.10	.00	12.75

NOTE.—Observations = 1,314 (wave 1), 1,064 (wave 2), 591 (wave 3).

the analysis we standardize each score to have mean 0 and standard deviation 1.[6]

Noncognitive skills are measured through parental assessment. In all three waves parents were asked 25 questions about children's behavior. Answers to each question can take three values: 1, Not true; 2, Somewhat true; 3, Certainly true.

[6] The PPVT and MRT tests are copyright protected, and we cannot include an example in the paper. However, we had a chance to see (and even attempt) the

Starting from the 25 questions, we construct measures of noncognitive skill by using iterated principal factor analysis. In table 5 we show the rotated factor loadings.[7] At each wave we retain three factors (those whose eigenvalues are larger than one). In the table we set in boldface the factor loadings larger than 0.25 in absolute value: the larger is the factor loading the larger is the correlation between the variables (rows) and factors (columns). The loadings are remarkably stable across waves.

Based on the factor loadings, we interpret the first factor as an index of behavioral problems such as restlessness, overactivity, short attention span, and temper problems. The second factor seems to capture empathy, kindness, and friendliness. Finally, we interpret the third factor as an index of poor self-esteem, insecurity, shyness, and depression (a range of emotional problems). These kind of noncognitive skills are similar to those measured by Cunha and Heckman (2008). For clarity, in the rest of the paper we will use a single term to describe each factor, namely: factor 1: index of behavioral problems; factor 2: index of good relationships with others; and factor 3: index of emotional problems. Each factor is standardized to have mean zero and standard deviation one and ordered so that a higher score corresponds to better noncognitive skills, that is, fewer behavioral or emotional problems and better relationships with others.

2. *Other Variables of Interest*

The LSAC is a very rich data set. A great deal of information was collected about the child, as well as his or her household, home, and school environments. In table 6 we report basic statistics for a few selected variables. The sample is evenly split between girls and boys. Parents were on average in their early thirties at the time of their child's birth, with fathers about 2 years older than mothers. Father's income is substantially larger than mother's income (as a relatively low proportion of mothers work full time in Australia). The percentage of indigenous children is unfortunately very small: it was quite difficult to contact and follow those living in remote areas. Table 7 shows mothers' education, and the order in the table reflects the ranking of qualifications. Achieving year 12 is equivalent to graduating from high school. Certificates represent vocational qualifications post–high school.

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tests. Our impression is that they do capture different types of skills. More information about the Peabody Picture Vocabulary Test can be found at http://www.pearsonpsychcorp.com.au/productdetails/242 (PPVT-4) and information about the Matrix Reasoning Test can be found at http://www.pearsonpsychcorp.com.au/productdetails/46.

[7] Note that only two questions changed between waves 1 and 2, while between waves 2 and 3 there was no change. In the two cases where the question changed across waves, we show both wave 1 and 2/3 questions separated by a double vertical line.

Table 5
Noncognitive Skills Loading Factors—All Waves

	Wave 1			Wave 2			Wave 3		
	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
Considerate of other people's feelings	**.2603**	**.5533**	−.0066	.2149	**.6164**	.0332	.2324	**.6071**	.0933
Shares readily with other children	.1632	**.4441**	.0841	.1319	**.4848**	.0851	.1382	**.5446**	.0891
Helpful if someone is hurt, upset, or feeling ill	.0560	**.5393**	.0468	.0184	**.5828**	.0294	.0454	**.6201**	.0216
Kind to younger children	.1091	**.4941**	.0615	.0773	**.5039**	.0739	.0639	**.5607**	.0539
Often volunteers to help others	.0648	**.5362**	−.0462	.1073	**.5500**	−.0695	.1607	**.4963**	−.0673
Restless, overactive, cannot stay still for long	**.7154**	.0732	.0265	**.7211**	.0711	.0675	**.7064**	.0698	.1058
Constantly fidgeting or squirming	**.6559**	.0330	.0970	**.7082**	.0455	.0970	**.6775**	.0424	.1580
Easily distracted, concentration wanders	**.6156**	.1198	.0933	**.6435**	.1136	.1172	**.6565**	.1190	.1221
Thinks things out before acting	**.2984**	**.3888**	−.0735	**.3952**	**.3463**	−.0299	**.4820**	**.3562**	−.0018
Good attention span	**.4629**	**.3282**	−.0730	**.5351**	**.2902**	.0187	**.5843**	**.2665**	.0096
Often complains of sickness	.1487	−.0270	**.2734**	.0644	−.0343	**.3246**	.1691	−.0167	**.3180**
Many worries, often seems worried	.0840	−.0542	**.5012**	.1068	.0037	**.5793**	.1161	.0066	**.5922**
Often unhappy, depressed, or tearful	.1804	.0317	**.4174**	.1691	.0960	**.4380**	.1581	.0950	**.5096**
Nervous or clingy in new situations	.0544	.1010	**.4251**	.0821	.0667	**.3871**	.0880	.0989	**.4374**
Many fears, easily scared	.1260	.0599	**.5099**	.1404	.0142	**.5298**	.1230	.0494	**.5321**
Often has temper tantrums or hot tempers	**.4754**	.1692	.1788	**.3829**	.1929	**.2895**	**.3524**	.2372	**.2848**
Generally well behaved, does what adults request	**.4060**	**.4271**	.0211	**.3828**	.4509	.0797	**.4137**	**.4386**	.0805
Often fights with other children or bullies them	**.3962**	.1795	.2449	**.2736**	.2437	**.2691**	**.2803**	.2170	**.2990**
Often argumentative with adults ‖ Often lies or cheats	**.4469**	.1454	.1802	**.3263**	.1383	.1863	**.4004**	.1732	.2033
Can be spiteful to others ‖ Steals	**.3149**	.1628	.2492	.1820	.1078	.1696	**.2681**	.0873	.1690
Rather solitary, tends to play alone	.0389	.1162	**.3703**	.0661	.1028	**.3842**	.0815	.1148	**.3569**
Has at least one good friend	.0193	**.3349**	.1628	.0480	**.2870**	.2495	.1460	**.2944**	.2205
Generally liked by other children	.0806	**.4599**	.2372	.1497	**.4356**	**.3062**	.2227	**.4280**	**.3355**
Picked on or bullied by other children	.1320	.0300	**.3644**	.1763	.0634	**.4052**	.2378	.0680	**.4418**
Gets on better with adults than with other children	.1253	.0007	**.4014**	.1032	.0625	**.3921**	.1233	.0894	**.4170**

Note.—Factor loadings that are larger than .25 in absolute value are in bold. Factor 1 = index of behavioral problems; factor 2 = index of good relationships with others; factor 3 = index of emotional problems. In the two cases where the question changed across waves, we show both wave 1 and 2/3 questions separated by a double vertical line.

Table 6
Demographics

	Wave 1		Wave 2		Wave 3	
Variable	Mean	SD	Mean	SD	Mean	SD
Girls	.46	.50	.49	.50	.51	.50
SC age (in months)	56.91	2.55	81.73	2.75	105.47	2.76
Mother's age	35.20	4.83	37.31	4.91	39.59	4.94
Father's age	37.49	5.45	40.00	6.06	41.74	5.66
Two biological parents	.89	.31	.86	.34	.84	.37
Grandparent at home	.03	.18	.04	.20	.03	.17
No. of siblings	1.43	.94	1.49	.91	1.54	.91
Father's annual income	5.81	4.31	6.49	4.46	7.75	5.86
Mother's annual income	2.28	2.11	2.93	2.90	3.29	2.55
SC is indigenous	.02	.12	.02	.13	.02	.15

NOTE.—Father and mother annual income is divided by 10,000. SC stands for study child.

Table 7
Mother Education

	Wave 1		Wave 2		Wave 3	
Variable	%	Cum	%	Cum	%	Cum
Year 8/below	.69	.69	.57	.57	.68	.68
Year 9	1.53	2.22	1.04	1.61	1.19	1.87
Year 10	8.03	10.25	7.76	9.37	5.78	7.65
Year 11	5.81	16.07	5.39	14.76	6.29	13.95
Year 12	15.07	31.14	15.14	29.90	14.46	28.40
Other degree	1.30	32.44	1.70	31.60	1.87	30.27
Certificate	22.11	54.55	25.92	57.52	26.70	56.97
Advanced degree	8.88	63.43	9.46	66.98	9.01	65.99
Bachelor	21.12	84.54	18.16	85.15	16.16	82.14
Grad diploma	7.50	92.04	7.47	92.62	9.86	92.01
Postgraduate	7.96	100.00	7.38	100.00	7.99	100.00

NOTE.—Cum = cumulative.

3. *Derived Indicators of Parenting Style*

The LSAC questionnaire asked both parents a set of questions describing their behavior toward the child. We identify 17 questions, common across waves, that are related to parenting style (see table 8, col. 1). We factor analyze the answers reported by the mother to derive a concise set of indicators of parenting style.[8]

Table 8 shows the rotated loading coefficients. The factor loadings larger than 0.25 in absolute value are set in bold. As with noncognitive skills, the factor loadings are very stable across waves. We interpret the

[8] We use only the mother's answer to account for those children with only one biological parent (mostly the mother). We select factors with an eigenvalue larger than 1.2.

Table 8
Home Environment Loading Factors, K Cohort—All Waves

Variable	Wave 1 Factor 1	Wave 1 Factor 2	Wave 2 Factor 1	Wave 2 Factor 2	Wave 3 Factor 1	Wave 3 Factor 2
Display physical affection	**.5740**	−.0297	**.7369**	−.0087	**.7538**	−.0445
Hug SC	**.6537**	.0112	**.6863**	.0014	**.6910**	−.0342
Express happiness to SC	**.7107**	−.0645	**.7104**	−.0905	**.7404**	−.0967
Warm encounters with SC	**.7047**	−.0270	**.7766**	−.0399	**.8078**	−.0614
Enjoy doing things with SC	**.6590**	−.0978	**.6941**	−.1021	**.7299**	−.1474
Close when happy or upset	**.6713**	−.0994	**.7246**	−.1054	**.7342**	−.1348
Explains correction	**.4554**	−.1460	**.4446**	−.1076	**.4230**	−.0457
Reasons when misbehaves	**.4786**	−.1067	**.4860**	−.0668	**.4498**	−.0648
Make sure completes requests	.1869	**−.3073**	.1799	−.2409	.1608	−.2350
Punish SC	.0131	**−.3546**	.0329	**−.2982**	.0348	**−.3224**
SC gets away unpunished	.0033	**.6796**	−.0330	**.7138**	−.0834	**.6797**
SC gets out of punishment	.0195	**.6814**	−.0179	**.6651**	−.0439	**.6507**
SC ignores punishment	−.1180	**.6791**	−.0462	**.7027**	−.0970	**.7100**
Praise behavior	**.4210**	−.1773	**.4513**	−.1865	**.4858**	**−.2713**
Disapprove of behavior	−.2445	**.3467**	−.2250	**.4193**	**−.3271**	**.4024**
Angry when punishing	−.2071	**.3263**	−.1900	**.3561**	−.1780	**.3290**
Have problems managing	−.2367	**.5044**	−.1690	**.5695**	−.2111	**.5626**

NOTE.—Factor loadings that are larger than .25 in absolute value are in bold. SC stands for study child. Factor 1 = index of mother warmth; factor 2 = index of effective mother discipline.

first factor as an index of mother warmth and affection. The second factor is strongly correlated with situations where the child ignores punishment and the mother has problems managing the child. Therefore, we interpret this factor as an index of the mother's effectiveness in imposing discipline. Note that the questions that load on this factor capture not simply lack of discipline but also inconsistency and harshness in how discipline is imposed (this is why we adopt the description "(in)effective" rather than "lenient"). To help exposition, we change the sign of the second factor, so a large value corresponds to effectiveness. In the rest of the paper we refer to these two factors as factor 1, index of mother warmth, and factor 2, index of effective mother discipline. We include these two measures of parenting style in the regression analysis.

We can find only a few papers in economics (Dooley and Stewart 2007; Cosconati 2009; Bjorklund, Lindahl, and Lindquist 2011) that use these kind of variables when investigating the determinants of child development. Yet the developmental psychology literature has investigated the link between parenting style and skills, particularly the noncognitive ones, since the early 1960s (see Baumrind [1966], Weiss and Schwarz [1996], and Hart, Newell, and Olsen [2003] for a discussion).

III. Estimation

In equation (2), we wrote the production function for child cognitive and noncognitive development as depending on both time inputs (TI) and parental background characteristics (PB):

$$Y_{ia} = TI'_{i\{K\times a\}}\beta_{\{K\times a\}} + PB'_{i\{G\times a\}}\delta_{\{G\times a\}} + e_{ia}.$$

However, identification of equation (2) is complicated by endogeneity of the time inputs (*TI*). Therefore, we estimate our production function under alternative estimators that attempt to deal with endogeneity in different ways. The estimators we choose are based closely on the discussion in Todd and Wolpin (2003, 2007). Below we briefly review the chosen estimators and their assumptions.

A. OLS Using Contemporaneous Inputs Only (CT)

This is arguably the most common specification in the literature. In this model only current (age *a*) inputs are included. The estimating equation becomes

$$Y_{ia} = TI'_{ia\{K\}}\beta_{a\{K\}} + PB'_{ia\{G\}}\delta_{a\{G\}} + e_{ia},$$

where *TI* and *PB* are, respectively, a *K* vector of observed time inputs and a *G* vector of parental background characteristics. The key assumptions behind this model are:

Only current time inputs matter.

$PB_{ia\{G\}}$ is a good proxy for any unobserved inputs as well as innate ability μ_i.

Thus, the OLS estimator relies on a rich set of control variables (*PB*) to proxy for μ_i, thereby dealing with the endogeneity that arises if allocations are correlated with innate ability. This assumption is arguably more plausible in the LSAC than in most data sets previously used to study child development, because of the very rich set of controls that are collected (particularly the home environment measures).

B. Contemporaneous + Lagged Test Score (VA)

This specification is known in the literature as value added. It is identical to CT but for the inclusion of the lagged test score as a control variable. Intuitively, the lagged score acts as a proxy for unobserved innate ability μ. The estimating equation becomes

$$Y_{ia} = TI'_{ia\{K\}}\beta_{a\{K\}} + PB'_{ia\{G\}}\delta_{a\{G\}} + \lambda_a Y_{i,a-1} + e_{ia}.$$

Although this specification may seem to be a clear improvement over the contemporaneous one, it also requires some strong assumptions. Namely,

The effect of inputs (observed or unobserved) declines with age at the rate λ_a.

The effect of μ_i declines with age at the rate λ_a.

A few steps of algebra are needed to understand these assumptions. For the sake of brevity we refer the reader to Todd and Wolpin (2007, 98–99).

C. Fixed Effects (FE)

Within-child fixed effects (or first differences) is another popular specification whenever longitudinal data are available. The estimating equation becomes

$$\Delta Y_{ia} = \Delta TI'_{ia\{K\}}\beta_{\{K\}} + \Delta PB'_{ia\{G\}}\delta_{\{G\}} + \Delta e_{ia}.$$

Here one differences out the scalar μ_i rather than attempt to control (or proxy) for it. The key assumptions behind this model are:

Strict exogeneity of inputs with respect to e_{ia} (i.e., e_{ia-1} cannot affect inputs at a).

The effect of observed inputs is constant by age.

The effect of μ_i is constant by age.

The omitted inputs and their effect are constant with age.

D. Contemporaneous + Lagged Inputs (CU)

This specification (also known as the cumulative model) expands the contemporaneous specification to include observable lagged inputs. Thus, it relaxes the assumption that only current inputs matter:

$$Y_{ia} = TI'_{i\{K\times a\}}\beta_{\{K\times a\}} + PB'_{i\{G\times a\}}\delta_{\{G\times a\}} + e_{ia},$$

where TI and PB are now a $K \times a$ matrix of observed time inputs and a $G \times a$ matrix of parental background characteristics. The key assumption behind this model is:

$PB_{i\{G\times a\}}$ is a good proxy for any unobserved inputs as well as innate ability μ_i.

E. Contemporaneous + Lagged Inputs + Lagged Test (CV)

This specification is a combination of the cumulative and value-added models. It generalized the value-added model by relaxing the assumption that the effect of observed inputs declines at rate λ_a. The estimating equation becomes

$$Y_{ia} = TI'_{i\{K\times a\}}\beta_{\{K\times a\}} + PB'_{i\{G\times a\}}\delta_{\{G\times a\}} + \lambda_a Y_{i,a-1} + e_{ia}.$$

The key assumption behind this model is now:

The effect of μ_i and unobserved inputs declines with age at the rate λ_a.

This model was preferred in Todd and Wolpin (2007), as we discuss below.

F. Discussion

Among the estimators that we include, CT, VA, and CU are nested within CV. Yet as Todd and Wolpin (2003, 2007) point out, it is difficult to argue in favor of any one model unless the researcher has strong priors on the set of assumptions needed to justify each. Most papers present results for a range of estimators, choose a "preferred" model based on some criterion, and then focus on the estimates from that model to draw policy conclusions. For example, in their 2007 paper Todd and Wolpin pick the CV model because it minimizes the out-of-sample root mean-squared error (RMSE).

In contrast, we are not interested in choosing a preferred model per se, as any criterion we might use to do so would necessarily be controversial. Rather, we are interested in whether there exists an estimator-robust ranking of the time inputs.[9] As the set of estimators that we consider encompasses the most widely used econometric techniques in this literature, finding a ranking that does not depend on the chosen estimator would be extremely encouraging. Such a ranking, if it exists, implies that a reallocation of time use can enhance child development.

Some of our estimators are demanding in terms of data. In particular, except for the CT model, they all require panel data. But children included in one wave of our sample are not always included in the other waves, as they may have missing diary data in some years. Likewise children in the wave 2 sample are not always in the wave 1 sample. As a result, if we want to compute the CV estimator using all three waves we would be left with only about 200 observations. Given that we use about 40 control variables on the right-hand side, there would be few degrees of freedom left. For this reason we decided to use only waves 1 and 2 (the largest ones) in our main analysis. Hence, the results in Section IV are obtained using the wave 2 test scores and the wave 1 and 2 time inputs and controls. In the appendix we also show some of the results obtained using waves 2 and 3. We do not attempt to use all the three waves at once because the sample size would be too small. Since the MRT test score was not administered at wave 1 we cannot, in principle, compute the value added (VA, CV) and fixed effect (FE) estimators for this test. Instead, we use the Who Am I? test as a proxy for the lagged MRT test score. In other words, the wave 1 WAI test proxies for lagged ability, rather than the lagged MRT test. The results in the VA, FE, and CV columns should be interpreted accordingly.

Finally, it would also be natural to consider an IV approach. However, as discussed earlier, we would need to find $K - 1 = 8$ valid instruments for the time inputs. This is not a feasible task in our application. If our main concern is the endogeneity of the time inputs arising from the correlation

[9] Of course, such a robust ranking is not necessarily the true one, as it is possible that all these estimators are inconsistent. For the same reason, a ranking that is rejected by one or more estimators is not necessarily false.

with the scalar μ_i, it is more practical to attempt to control or proxy for μ_i using one of the five common estimators described here.

IV. Results

Tables 9–13 present our estimation results for cognitive and noncognitive skills. Because the nine time inputs are collinear, we take educational activities with parents (*ped*) as the omitted category. Hence, the coefficients of the other $K - 1$ time inputs should be interpreted as their effect relative to that of educational activities with parents. Asterisks indicate whether these relative effects are significant at the 5% and 10% levels. We also report the F-test for the null hypothesis of equality of all the wave 2 time input coefficients.

Of course, the estimates in tables 9–13 do not directly show the ranking of the K time inputs: they do not show whether, for instance, time spent using media has a statistically different effect from time spent in social activities. To fill this gap we construct a second set of tables (see appendix tables A1, A2), where in the left column the time inputs are ranked from most to least productive and where the cells show the difference between any pair of time inputs together with its statistical significance. Thus, the coefficients in these tables are independent of which time input is the omitted category. Next, we discuss separately the results for cognitive and noncognitive skills.

A. Cognitive Skills

1. Peabody Picture Vocabulary Test (PPVT)

Table 9 shows the estimated coefficients for the PPVT test score, while table A1 describes the ranking of the time input coefficients. With the exception of the FE estimator we reject the hypothesis that the wave 2 time inputs are equally productive. Educational activities with parents (*ped*) and with adults other than parents (*oed*) appear to be the most productive inputs. That is, in table 9 the coefficients on other activities are typically negative, implying that they are less productive than *ped* and *oed*. And in table A1 *ped* and *oed* rank as the top two time inputs for all estimators except fixed effects.

The problem with fixed effects is that the estimates are too imprecise (due to the efficiency loss that results from differencing) for the rank differences to be significant. Still, the point estimates imply that educational time with adults is among the most productive inputs.

On the other hand, time spent in general care activities with parents (*pcr*) or with other adults (*ocr*) is generally found in the bottom half of the ranking. The results have clear implications for the impact of time reallocations. For instance, the CT estimator suggests that 1 more hour a week spent in educational activities with parents (*ped*) rather than in general care (*pcr*) would increase the PPVT test score by 0.034 standard deviations. It is

Table 9
Production Function—PPVT

	CT	VA	FE	CU		CV	
				Wave 2	Wave 1	Wave 2	Wave 1
pcr	−.034**	−.036**	−.011	−.056**	.001	−.055**	.002
	(.009)	(.009)	(.007)	(.016)	(.006)	(.015)	(.006)
sch	−.045**	−.051**	−.016**	−.063**	.004	−.054**	.006
	(.011)	(.012)	(.006)	(.021)	(.005)	(.019)	(.005)
oed	−.004	.002	.015	−.021	−.023	−.004	−.028
	(.034)	(.035)	(.028)	(.042)	(.023)	(.038)	(.026)
ocr	−.040**	−.040**	−.016	−.073**	.005	−.065**	.006
	(.012)	(.012)	(.010)	(.020)	(.010)	(.019)	(.010)
soc	−.027**	−.032**	−.005	−.054**	−.006	−.053**	−.007
	(.008)	(.009)	(.007)	(.015)	(.006)	(.014)	(.006)
mda	−.022**	−.026**	.001	−.035*	−.010	−.030*	−.009
	(.009)	(.010)	(.010)	(.019)	(.010)	(.017)	(.010)
bed	−.045**	−.046**	.002	−.048**	−.023**	−.046**	−.020**
	(.010)	(.010)	(.010)	(.019)	(.010)	(.017)	(.009)
unk	−.039*	−.028	−.021	−.055	.002	−.050	.005
	(.021)	(.021)	(.015)	(.042)	(.015)	(.036)	(.013)
Girl	−.110*	−.189**	(dropped)	−.217**		−.202**	
	(.059)	(.062)		(.107)		(.103)	
Child age (months)	.032**	.018	.018	.033*		.024	
	(.011)	(.011)	(.021)	(.019)		(.018)	
Mother age	.023**	.018**	−.146	.007		.002	
	(.007)	(.008)	(.246)	(.015)		(.014)	
Father age	−.003	−.004	−.018	−.009		−.013	
	(.006)	(.006)	(.062)	(.012)		(.012)	

Two biological parents	.380**	.307**	−.169	.399		.557**	
	(.140)	(.139)	(.779)	(.383)		(.270)	
Grandparent at home	−.221	−.275	−.160	.090		−.030	
	(.188)	(.222)	(.287)	(.230)		(.225)	
Number of siblings	−.118**	−.068*	.007	−.082		−.064	
	(.036)	(.036)	(.169)	(.068)		(.064)	
Max{M Ed, F Ed}	.063**	.058**	−.040	.071**		.064**	
	(.011)	(.012)	(.071)	(.023)		(.021)	
Father annual income	.014**	.012	.005	−.005	.020	−.005	.022
	(.007)	(.007)	(.018)	(.014)	(.021)	(.014)	(.021)
Mother annual income	.008	.004	−.016	−.020	−.006	−.019	−.003
	(.010)	(.011)	(.023)	(.024)	(.029)	(.021)	(.028)
Child is indigenous	−.215	−.083	(dropped)	.306		.464	
	(.198)	(.248)		(.469)		(.449)	
Mother warmth	−.004	−.010	−.024	.053	−.117*	.020	−.066
	(.032)	(.032)	(.064)	(.067)	(.067)	(.066)	(.068)
Mother discipline	.093**	.048	−.092	.057	.184**	.009	.153**
	(.031)	(.032)	(.066)	(.061)	(.065)	(.063)	(.066)
Lagged score		.307**					.315**
		(.034)					(.055)
$r2_a$	.134	.217	.040		.132		.222
N	1,033	871	786		400		382
N regressors	42	43	35		67		68
F-test wave 2 time inputs	3.799**	3.408**	1.445	2.801**		2.939**	
F-test lagged inputs					4.451**		9.697**
F-test fixed effects			2.2e+05**				

NOTE.—Standard errors in parentheses. Each regression also includes state of residence and mother's first language dummies: wave 2 values only in CT and VA; waves 2 and 1 values in FE, CU, and CV. Max{M Ed, F Ed} = max years of education between mother and father. F-test on lagged inputs does not include lagged score.

* Significant at the 10% level.

** Significant at the 5% level.

also noteworthy that time spent using media (*mda*) is a more valuable input than time in before/after school care (*sch*).

Among the control variables, the estimate of the parental education coefficient is consistently positive, implying that an extra year of education raises scores by about .06 to .07 standard deviations across estimators. The exception is fixed effects, where the education coefficient is imprecisely estimated and has the wrong sign. Girls score consistently lower than boys on the PPVT by .10 to .20 standard deviations. Most of the other controls have the expected sign, but they are not always significant depending on the estimator.

The coefficient on the lagged test score is about 0.31 and highly significant in both the VA and CV models. Other lagged control variables do not seem to be especially important: they are jointly significant but the adjusted R-squared does not increase much when they are added. Nevertheless, in the CU and CV models the lagged coefficient on mother effective discipline is positive and quantitatively large.

To get a sense of how important time allocation is relative to the background variables (like parental education) we consider the following comparison: according to the CT estimator, the effect of having 2 more hours a week in educational activities with parents, rather than 1 hour in general care with other adults (*ocr*) and 1 hour in social activities (*soc*), is a $0.040 + 0.027 = 0.067$ standard deviation increase in the PPVT score. This is about the same as the 0.063 standard deviation increase produced by 1 additional year of parental education.

2. *Matrix Reasoning Test* (*MRT*)

Table 10 shows the results for the MRT test, while table A2 presents the ranking of the time input coefficients. Overall the results are quite similar to those for the PPVT test. For instance, educational activities with parents (*ped*) and educational activities with other adults (*oed*) are always near the top of the rankings. Time spent in general care activities with parents (*pcr*) is generally near the bottom of the rankings. As with the PPVT, only in the case of the FE estimator do we fail to reject the null hypothesis that the wave 2 time inputs are all equally productive ($p = .116$).

According to the CT estimator, the effect of having 2 more hours a week in educational activities with parents, rather than 1 hour in general care with other adults (*ocr*) and 1 hour in social activities (*soc*), is $0.016 + 0.019 = 0.035$. This is again comparable to the 0.039 standard deviation increase produced by 1 additional year of parental education. And, as with the PPVT, the lagged control variables are statistically significant, but their inclusion has little impact on the adjusted R-squared.

However, there are also some differences from the PPVT test score results. For example, time spent in before/after school care always ranks higher for the MRT test score than for the PPVT, while time sleeping/napping now ranks consistently as the least productive input (of course, all the results only apply within the range of variation in the data: obviously one could not increase scores by substituting all sleep time with educational time).[10] Among the control variables, the child's gender is no longer significant, but child age is (older children scoring higher). The coefficient on the lagged score is large and highly significant, even though we are actually using the WAI test score rather than the lagged MRT score. This result suggests that lagged ability is still a good predictor for current test scores. The lagged indicator of mother effective discipline is no longer significant.

B. Noncognitive Skills

1. Behavioral Problems

Table 11 show the results for the index of behavioral problems (ordered so a higher score means fewer problems). The findings for this dimension of noncognitive skill are very different from those for cognitive skills. With the exception of the CV estimator, the *F*-test provides little evidence of significant differences in the effect of the time inputs. For this reason we omit the supplementary table that describes the ranking of the time inputs. Among the control variables, parental education is never statistically significant, and girls have much better scores than boys. The coefficient on mother effective discipline is now consistently positive and quantitatively large across all five estimators (meaning that more effective discipline leads to fewer behavioral problems). The lagged behavioral test score is more important than for cognitive skills, suggesting that there is more persistence in the index of behavioral problems than in cognitive skills.

2. Good Relationships

The findings for the index of good relationships are reported in table 12. The results are similar to those for behavioral problems. There is little or no evidence that the time allocation matters for this dimension of noncognitive skill. Girls score better than boys, mother effective discipline has a positive effect on the index, and the lagged score is statistically significant and large in magnitude. The main difference with the index of behavioral problems is that now the factor capturing mother warmth is also very important.

3. Emotional Problems

Finally, table 13 shows the results for the index of emotional problems (where a higher score means fewer problems). Consistent with the other two indexes of noncognitive skills, we find that time allocation is of no

[10] Table 4 shows that at wave 2 the average child was spending 76.43 weekly hours in bed, or about 11 hours a day, with a standard deviation of 5.34 hours per week, or .76 hours per day. Thus, a two standard deviation range of sleep hours is roughly 10 1/4 to 11 3/4 per day.

Table 10
Production Function—MRT

	CT	VA	FE	CU		CV	
				Wave 2	Wave 1	Wave 2	Wave 1
pcr	−.027**	−.021**	−.006	−.052**	−.010	−.049**	−.007
	(.009)	(.009)	(.007)	(.017)	(.007)	(.016)	(.007)
sch	.004	.003	−.009	−.025	−.008	−.025	−.004
	(.011)	(.012)	(.007)	(.022)	(.006)	(.021)	(.006)
oed	.032	.037	.006	−.001	−.017	.003	−.020
	(.043)	(.044)	(.019)	(.046)	(.020)	(.046)	(.019)
ocr	−.016	−.012	−.009	−.035	−.003	−.024	.001
	(.012)	(.014)	(.010)	(.023)	(.009)	(.023)	(.009)
soc	−.019**	−.014	−.009	−.046**	−.015**	−.048**	−.010
	(.008)	(.009)	(.007)	(.017)	(.007)	(.017)	(.007)
mda	−.018*	−.007	.004	−.045**	−.012	−.040**	−.008
	(.009)	(.010)	(.010)	(.018)	(.009)	(.018)	(.008)
bed	−.035**	−.031**	−.018	−.062**	−.013	−.061**	−.006
	(.010)	(.010)	(.011)	(.019)	(.011)	(.019)	(.011)
unk	−.026	−.017	.021*	−.041	−.010	−.037	−.012
	(.020)	(.022)	(.012)	(.035)	(.014)	(.035)	(.013)
Girl	.114*	.000	(dropped)	.029		−.170	
	(.061)	(.069)		(.117)		(.120)	
Child age (months)	.061**	.044**	.016	.068**		.045**	
	(.011)	(.012)	(.016)	(.019)		(.019)	
Mother age	.004	.006	−.021	.007		.004	
	(.008)	(.008)	(.181)	(.017)		(.016)	
Father age	−.007	−.006	−.160**	−.016		−.013	
	(.006)	(.006)	(.050)	(.014)		(.013)	
Two biological parents	.254*	.175	2.615**	−.126		.030	
	(.153)	(.163)	(.678)	(.350)		(.378)	

Grandparent at home	−.102	−.012	.119	−.004		.173	
	(.147)	(.155)	(.410)	(.299)		(.273)	
Number of siblings	−.049	−.049	.029	−.110		−.088	
	(.032)	(.033)	(.161)	(.067)		(.062)	
Max{M Ed, F Ed}	.039**	.035**	.123	.032		.030	
	(.012)	(.012)	(.081)	(.023)		(.022)	
Father annual income	.008	.005	−.004	−.013	.016	−.015	.012
	(.009)	(.009)	(.016)	(.012)	(.020)	(.012)	(.020)
Mother annual income	−.006	−.009	.021	−.011	.023	−.007	.002
	(.011)	(.012)	(.029)	(.023)	(.033)	(.023)	(.032)
Child is indigenous	−.395**	−.407*	(dropped)	−.428**		−.329	
	(.167)	(.208)		(.204)		(.251)	
Mother warmth	.009	.006	−.041	−.010	−.028	.000	−.024
	(.033)	(.034)	(.071)	(.072)	(.071)	(.073)	(.069)
Mother discipline	.038	.027	.000	.059	.044	.063	.009
	(.031)	(.032)	(.064)	(.068)	(.070)	(.066)	(.069)
Lagged score		.258**					.339**
		(.036)					(.060)
$r2_a$	.078	.130	.076		.074		.153
N	1,054	940	807		403		400
N regressors	42	43	35		67		68
F-test wave 2 time inputs	3.817**	2.839**	1.174	1.986**		2.043**	
F-test lagged inputs					3.199**		4.182**
F-test fixed effects			41.299**				

NOTE.—Standard errors in parentheses. Each regression also includes state of residence and mother's first language dummies: wave 2 values only in CT and VA; waves 2 and 1 values in FE, CU, and CV. Max{M Ed, F Ed} = max years of education between mother and father. F-test on lagged inputs does not include lagged score.

* Significant at the 10% level.

** Significant at the 5% level.

Table 11
Production Function—Behavioral

	CT	VA	FE	CU		CV	
				Wave 2	Wave 1	Wave 2	Wave 1
pcr	−.017**	−.003	.002	−.028	.005	−.015	−.001
	(.009)	(.008)	(.005)	(.018)	(.008)	(.014)	(.006)
sch	−.008	−.002	−.004	−.009	.003	−.004	.005
	(.011)	(.010)	(.005)	(.022)	(.007)	(.016)	(.006)
oed	−.012	−.014	.011	−.128*	−.015	−.088**	−.015
	(.049)	(.031)	(.015)	(.068)	(.023)	(.044)	(.018)
ocr	−.014	−.012	.003	−.008	−.007	−.008	−.005
	(.013)	(.013)	(.007)	(.023)	(.011)	(.020)	(.008)
soc	−.004	.003	−.001	−.011	−.005	.000	.001
	(.008)	(.007)	(.006)	(.017)	(.007)	(.013)	(.006)
mda	−.009	.001	−.004	−.012	−.001	−.007	.003
	(.008)	(.008)	(.007)	(.019)	(.011)	(.015)	(.009)
bed	−.006	−.000	−.001	−.021	−.009	−.008	−.002
	(.009)	(.009)	(.008)	(.020)	(.011)	(.016)	(.009)
unk	−.015	−.023	−.007	−.127**	.013	−.093**	.011
	(.022)	(.023)	(.009)	(.044)	(.011)	(.029)	(.010)
Girl	.216**	.111**	(dropped)	.196*		.111	
	(.060)	(.053)		(.114)		(.096)	
Child age (months)	.003	−.005	−.018	−.019		−.025	
	(.011)	(.009)	(.014)	(.019)		(.016)	
Mother age	.007	.001	.252	.003		−.001	
	(.007)	(.007)	(.165)	(.014)		(.012)	
Father age	.008	.003	−.024	−.006		−.007	
	(.005)	(.005)	(.050)	(.011)		(.010)	
Two biological parents	.099	.088	.552	.213		.344	
	(.162)	(.200)	(.745)	(.422)		(.310)	

Grandparent at home	.121	.111	−.132	.340		.242	
	(.162)	(.139)	(.089)	(.313)		(.270)	
Number of siblings	.022	.000	.085	.020		−.029	
	(.033)	(.032)	(.124)	(.068)		(.059)	
Max{M Ed, F Ed}	.015	.015	.029	.030		.016	
	(.012)	(.010)	(.057)	(.020)		(.016)	
Father annual income	.000	−.002	.006	.001	−.021	−.004	−.011
	(.008)	(.007)	(.011)	(.015)	(.023)	(.013)	(.019)
Mother annual income	−.013	−.018*	−.020	−.029	.009	−.026	.010
	(.010)	(.009)	(.021)	(.024)	(.036)	(.019)	(.028)
Child is indigenous	−.491**	−.267	(dropped)	−.517		−.157	
	(.233)	(.223)		(.381)		(.326)	
Mother warmth	.096**	.039	.034	.151*	−.031	.082	−.027
	(.031)	(.030)	(.060)	(.077)	(.073)	(.065)	(.063)
Mother discipline	.348**	.199**	.133**	.354**	.117*	.224**	−.029
	(.033)	(.032)	(.051)	(.061)	(.069)	(.058)	(.057)
Lagged score		.521**					.514**
		(.032)					(.057)
$r2_a$	.164	.415	.016		.192		.408
N	1,028	923	798		391		391
N regressors	42	43	35		67		68
F-test wave 2 time inputs	1.058	.535	.517	1.954 *		2.308**	
F-test lagged inputs					2.580**		1.497*
F-test fixed effects			345.465**				

Note.—Standard errors in parentheses. Each regression also includes state of residence and mother's first language dummies: wave 2 values only in CT and VA; waves 2 and 1 values in FE, CU, and CV. Max{M Ed, F Ed} = max years of education between mother and father. *F*-test on lagged inputs does not include lagged score.

* Significant at the 10% level.

** Significant at the 5% level.

Table 12
Production Function—Relationship

	CT	VA	FE	CU		CV	
				Wave 2	Wave 1	Wave 2	Wave 1
pcr	−.004	.003	−.001	−.009	.003	−.008	.003
	(.008)	(.008)	(.006)	(.015)	(.007)	(.012)	(.006)
sch	−.003	−.003	−.002	−.009	−.001	−.027*	.003
	(.010)	(.010)	(.006)	(.019)	(.006)	(.016)	(.005)
oed	−.006	−.005	.013	.020	−.011	.001	−.013
	(.024)	(.020)	(.016)	(.040)	(.022)	(.042)	(.017)
ocr	−.016	−.007	.006	.003	−.010	.002	−.008
	(.013)	(.013)	(.008)	(.022)	(.009)	(.021)	(.008)
soc	.005	.006	.003	.008	−.000	.002	−.000
	(.008)	(.007)	(.007)	(.015)	(.007)	(.013)	(.006)
mda	.000	.009	−.000	.014	−.003	.012	.006
	(.009)	(.008)	(.008)	(.017)	(.011)	(.013)	(.009)
bed	.002	.004	−.003	.009	−.002	.004	.006
	(.009)	(.008)	(.010)	(.017)	(.010)	(.014)	(.009)
unk	−.031*	−.013	.001	−.100**	−.006	−.092**	−.003
	(.017)	(.017)	(.014)	(.044)	(.017)	(.032)	(.016)
Girl	.293**	.231**	(dropped)	.180*		.168*	
	(.057)	(.054)		(.104)		(.093)	
Child age (months)	−.006	−.007	.007	−.010		−.008	
	(.011)	(.010)	(.015)	(.020)		(.017)	
Mother age	−.003	.003	−.034	.004		.011	
	(.007)	(.007)	(.173)	(.015)		(.013)	
Father age	−.005	−.013**	−.049	−.009		−.013	
	(.006)	(.005)	(.044)	(.013)		(.011)	
Two biological parents	.264	.397**	.940*	−.300		−.177	
	(.162)	(.187)	(.479)	(.529)		(.439)	

Grandparent at home	−.113	−.117	.003	.067		.022	
	(.169)	(.152)	(.407)	(.291)		(.246)	
Number of siblings	.034	.059*	.053	−.006		.020	
	(.033)	(.032)	(.151)	(.065)		(.055)	
Max{M Ed, F Ed}	−.000	−.000	−.067	−.016		−.015	
	(.011)	(.010)	(.064)	(.022)		(.018)	
Father annual income	−.009	−.006	−.014	−.019	.018	−.016	.023
	(.007)	(.007)	(.016)	(.017)	(.019)	(.015)	(.017)
Mother annual income	.007	.002	.019	.040*	−.019	.040**	.000
	(.009)	(.009)	(.023)	(.021)	(.029)	(.019)	(.025)
Child is indigenous	−.077	−.015	(dropped)	.038		.303	
	(.213)	(.213)		(.478)		(.485)	
Mother warmth	.299**	.191**	.204**	.322**	−.003	.272**	−.108
	(.031)	(.031)	(.061)	(.073)	(.080)	(.064)	(.067)
Mother discipline	.286**	.156**	.100	.248**	.081	.171**	−.008
	(.036)	(.037)	(.063)	(.080)	(.070)	(.067)	(.065)
Lagged score		.451**					.464**
		(.033)					(.053)
$r2_a$	.207	.375	.085		.205		.369
N	1,028	923	798		391		391
N regressors	42	43	35		67		68
F-test wave 2 time inputs	1.166	.679	.350	1.527		2.505**	
F-test lagged inputs					7.440**		10.825**
F-test fixed effects			368.541**				

NOTE.—Standard errors in parentheses. Each regression also includes state of residence and mother's first language dummies: wave 2 values only in CT and VA; waves 2 and 1 values in FE, CU, and CV. Max{M Ed, F Ed} = max years of education between mother and father. F-test on lagged inputs does not include lagged score.

* Significant at the 10% level.

** Significant at the 5% level.

Table 13
Production Function—Emotional

				CU		CV	
	CT	VA	FE	Wave 2	Wave 1	Wave 2	Wave 1
pcr	.014	.013	.000	.000	−.004	.012	−.002
	(.009)	(.009)	(.007)	(.017)	(.007)	(.016)	(.006)
sch	.018	.019*	−.001	−.007	.005	.008	.002
	(.012)	(.011)	(.007)	(.020)	(.006)	(.018)	(.005)
oed	−.018	−.017	−.038*	−.145**	.002	−.179**	.012
	(.039)	(.042)	(.020)	(.059)	(.018)	(.051)	(.015)
ocr	.015	.009	−.002	−.016	.007	−.004	.004
	(.015)	(.016)	(.009)	(.026)	(.009)	(.025)	(.008)
soc	.013	.016*	.008	.003	.002	.016	−.005
	(.009)	(.009)	(.008)	(.017)	(.007)	(.017)	(.006)
mda	.015	.014	−.001	−.013	.008	.004	.003
	(.010)	(.010)	(.009)	(.019)	(.009)	(.018)	(.008)
bed	.015	.012	−.005	−.008	.015	.002	.010
	(.010)	(.010)	(.010)	(.019)	(.010)	(.019)	(.010)
unk	.023	.017	−.001	.025	−.004	.034	−.003
	(.031)	(.034)	(.014)	(.049)	(.015)	(.048)	(.014)
Girl	−.048	−.041	(dropped)	−.015		−.006	
	(.062)	(.059)		(.113)		(.101)	
Child age (months)	−.011	−.005	−.020	.021		.020	
	(.011)	(.010)	(.014)	(.020)		(.017)	
Mother age	−.011	−.016*	.215	−.003		−.016	
	(.009)	(.009)	(.165)	(.016)		(.013)	
Father age	.008	.007	.011	.004		.016	
	(.007)	(.006)	(.045)	(.014)		(.011)	
Two biological parents	.178	.290	.063	.349		.201	
	(.256)	(.335)	(.583)	(.531)		(.519)	

Grandparent at home	−.114	−.096	.305	.210		.301	
	(.168)	(.165)	(.236)	(.305)		(.252)	
Number of siblings	.114**	.082**	−.094	.127*		.077	
	(.033)	(.033)	(.131)	(.070)		(.061)	
Max{M Ed, F Ed}	.010	−.002	.091	.013		.009	
	(.011)	(.011)	(.060)	(.022)		(.019)	
Father annual income	−.007	.001	.030**	.008	−.024	.019	−.030
	(.008)	(.008)	(.014)	(.015)	(.022)	(.014)	(.021)
Mother annual income	.026**	.014	−.027	.049**	.014	.016	.025
	(.011)	(.010)	(.021)	(.024)	(.030)	(.021)	(.027)
Child is indigenous	−.169	−.037	(dropped)	.156		.622	
	(.256)	(.276)		(.475)		(.411)	
Mother warmth	.040	.012	.042	−.026	.119	.018	.045
	(.032)	(.032)	(.065)	(.079)	(.074)	(.072)	(.065)
Mother discipline	.242**	.197**	.019	.153**	.037	.117	.061
	(.035)	(.035)	(.073)	(.077)	(.076)	(.072)	(.068)
Lagged score		.419**					.449**
		(.035)					(.060)
$r2_a$	.071	.240	.057		.069		.250
N	1,028	923	798		391		391
N regressors	42	43	35		67		68
F-test wave 2 time inputs	.555	.639	.981	1.223		2.481**	
F-test lagged inputs					15.522**		12.999**
F-test fixed effects			488.425**				

NOTE.—Standard errors in parentheses. Each regression also includes state of residence and mother's first language dummies: wave 2 values only in CT and VA; waves 2 and 1 values in FE, CU, and CV. Max{M Ed, F Ed} = max years of education between mother and father. F-test on lagged inputs does not include lagged score.

** Significant at the 5% level.

importance.[11] Once again, mother effective discipline has a positive effect on the index, and the lagged score is statistically significant and large in magnitude. There is no evidence of a gender effect in this case, while children with more siblings score better. Overall, the adjusted R-squared is lower than for the behavioral problems and relationship indexes.

C. Comparison between Cognitive and Noncognitive Skills

The results in Sections IV.A and IV.B indicate that the production functions for cognitive and noncognitive skills are very different. Cognitive skills are affected by the way children's time is allocated and by parental education. The effect of reallocating time across different activities is large and (in the plausible scenarios we considered) comparable in magnitude to the effect of 1 more year of parental education. But noncognitive skills seem insensitive to both the allocation of children's time and parental education. Instead we find they are strongly influenced by parenting style, specifically effective discipline and warmth. Adding these indicators of parenting style to the standard set of control variables does little for cognitive skills but strongly increases the adjusted R-squared for the noncognitive ones.

This result on the importance of parenting style for noncognitive skills appears to be new in the economics literature.[12] Nevertheless, it aligns with previous studies in developmental psychology which found that "authoritative" parenting (a warm, engaged, rational parent-child relationship) leads to fewer behavioral problems.[13] We also find that lagged scores are more predictive of noncognitive skills, suggesting stronger persistence in noncognitive skills (i.e., behaviors) than in cognitive skills, at least at young ages.

D. A Formal Test of Rankings

The main advantage of our study is the use of 24-hour time diaries. This allows explicit characterization of the trade-off between alternative activities.

[11] For the index of emotional problems, and to a less extent for the index of behavioral problems, the CV estimator's coefficient on *oed* is generally negative and very large. We refrain from interpreting this result as an indication that educational activities with adults other than parents might have a negative effect. It is possible that this coefficient is also picking up an effect of having less support from parents.

[12] Dooley and Stewart (2007) only look at noncognitive skills while Cosconati (2009) looks at the effect of one aspect of parenting style (i.e., time use constraints or curfews) on cognitive skills. Bjorklund et al. (2011) investigate the determinants of siblings' correlation in income. However, we are not aware of any prior study that both (i) uses broad measures of parenting style and (ii) compares effects on cognitive vs. noncognitive skills.

[13] Weiss and Schwarz (1996) find that authoritative parenting also leads to higher school grades, which contradicts our results on the PPVT and MRT. However, they study older adolescents, not young children.

The results in Section IV.A show that children's time allocation affects their cognitive development while having little impact on their social and emotional development. Therefore, in this section we focus on cognitive skills alone and investigate whether the data support a ranking(s) of the time inputs that cannot be statistically rejected across estimators.

We begin by testing the hypothesis that educational activities with parents (generally ranked at or near the top according to our point estimates) is more productive than three other inputs generally ranked in the bottom half: time in general care with parents or other adults and time sleeping/napping. Formally, our test can be written as

$$\begin{gathered} H_2: \beta_{ped} \geq \{\beta_{pcr}, \beta_{ocr}, \beta_{bed}\} \\ \text{vs.} \\ H_1: \{\beta_{ped}, \beta_{pcr}, \beta_{ocr}, \beta_{bed}\} \in \mathbb{R}^4. \end{gathered} \tag{3}$$

The implementation of this type of test is complicated by the fact that the null hypothesis contains a number of inequalities. Conventional two-sided and one-sided multivariate tests are not designed to address the hypothesis in (3). Wolak (1987, 1989) develops a test for examining the validity of linear inequality constraints on the parameters of linear econometric models. His procedure involves three steps. First, one solves

$$\min_b (Y - Xb)'(Y - Xb) \text{ subject to } Rb > r, \tag{4}$$

where X is the matrix of covariates (i.e., time inputs and parental background variables) and $Rb > r$ expresses the inequality constraints. Second, we compute the Wald statistic, using the restricted and unrestricted estimates together with the unrestricted estimate of the variance-covariance matrix. However, the Wald statistic has a $\bar{\chi}^2$ distribution: a weighted average of χ^2 cumulative distribution functions where the weights have to be computed or simulated.[14] The third and final step involves deriving the weights and computing the p-values accordingly.

Testing (3) is not sufficient however. Even if H_2 is not rejected, the null hypothesis could hold with equality. Because of the weak inequalities, the null hypothesis in (3) is a test for educational activities with parents being no worse than the other three time inputs (*pcr, ocr, bed*). Therefore, we complement (3) by testing the null hypothesis of equality versus weak inequality:

$$\begin{gathered} H_0: \beta_{ped} = \beta_{pcr} = \beta_{ocr} = \beta_{bed} \\ \text{vs.} \\ H_2: \beta_{ped} \geq \{\beta_{pcr}, \beta_{ocr}, \beta_{bed}\}. \end{gathered} \tag{5}$$

[14] Close form solutions for the weights exist only for rank $(R) \leq 4$.

Wolak (1987, 1989) also shows how to implement the test in (5). Hereafter we refer to the test in (3) as the "inequality versus unrestricted" (*IU*) test while we refer to the test in (5) as the "equality versus inequality" (*EI*) test. If we cannot reject the null in the *IU* test but we reject the null in the *EI* test then we can conclude that H_2 holds with at least one strict inequality. In our context, that would imply that educational activities with parents is no worse than the other three activities (i.e., time in general care with parents or other adults and time in bed), while at the same time being better than at least one of them. We also test a few permutations of the time inputs to see whether multiple rankings could be consistent with the data.

Tables 14 and 15 show the results for the PPVT and MRT test scores, respectively. The numbers in the table are the Wald statistics obtained by solving (4) subject to either (3) or (5), giving the the *IU* and *EI* tests, respectively. A Wald statistic of zero corresponds to the case where the restricted and unrestricted estimates are identical. Asterisks indicate whether the Wald statistics are significantly different from zero, with the *p*-values calculated as explained above.

The first ranking tested in tables 14–15 (Rnk1) is the one defined in (3). For both the PPVT and MRT test scores, the Wald statistic for the *IU* test is always zero or approximately zero, indicating that this ranking is strongly supported by the data. The Wald statistic for the *EI* test is always positive and statistically significant, indicating that the hypothesis of equality is strongly rejected. Together, these two results support the hypothesis that educational activities with parents are more productive than time in general care with parents or other adults and time in bed.

Table 14
Ranking Test—PPVT

	CT		VA		FE		CU		CV	
	IU	*EI*	*IU*	*EI*	*IU*	*EI*	*IU*	*EI*	*IU*	*EI*
Rnk1: *ped* > {*pcr*, *ocr*,*bed*}	.00	23.00**	.00	21.78**	.07	8.63**	.00	17.46**	.00	17.99**
Rnk2: *oed* > {*pcr*, *ocr*,*bed*}	.00	3.49	.00	3.07	.00	4.79	.00	2.45	.00	3.11
Rnk3: *ped* > {*pcr*, *ocr*,*bed*,*sch*}	.00	24.68**	.00	24.19**	.07	18.61**	.00	17.83**	.00	18.10**
Rnk4: *oed* > {*pcr*, *ocr*,*bed*,*sch*}	.00	4.34	.00	4.91	.00	8.86**	.00	2.70	.00	3.11
Rnk5: *ped* > *mda* > {*pcr*,*ocr*,*bed*}	.00	25.36**	.00	23.14**	.08	9.00**	.00	19.75**	.00	20.35**
Rnk6: *ped* > *mda* > {*pcr*,*ocr*,*bed*,*sch*}	.00	27.90**	.00	26.35**	.08	22.82**	.00	20.46**	.00	20.72**

NOTE.—Numbers in table are Wald statistics. *IU*: inequality vs. unrestricted test. *EI*: equality vs. inequality test.
* Significant at the 10% level.
** Significant at the 5% level.

Table 15
Ranking Test—MRT

	CT		VA		FE		CU		CV	
	IU	*EI*	*IU*	*EI*	*IU*	*EI*	*IU*	*EI*	*IU*	*EI*
Rnk1: *ped* > {*pcr*, *ocr*,*bed*}	.00	14.13**	.00	9.98**	.00	5.51*	.00	12.37**	.00	12.09**
Rnk2: *oed* > {*pcr*, *ocr*,*bed*}	.00	4.83	.00	4.67	.00	4.33	.00	2.28	.00	3.63
Rnk3: *ped* > {*pcr*, *ocr*,*bed*,*sch*}	.17	28.85**	.07	19.01**	.00	5.63	.00	15.26**	.00	14.23**
Rnk4: *oed* > {*pcr*, *ocr*,*bed*,*sch*}	.00	21.99**	.00	14.64**	.00	4.36	.00	5.53	.00	6.38
Rnk5: *ped* > *mda* > {*pcr*,*ocr*,*bed*}	.01	14.93**	.00	14.41**	.27	7.77**	.24	12.24**	.51	12.35**
Rnk6: *ped* > *mda* > {*pcr*,*ocr*,*bed*,*sch*}	7.50**	20.04**	1.29	19.87**	.00	9.25**	6.39*	8.64**	4.84	10.54**

NOTE.—Numbers in table are Wald statistics. *IU*: inequality vs. unrestricted test. *EI*: equality vs. inequality test.
* Significant at the 10% level.
** Significant at the 5% level.

In the second ranking (Rnk2), we replace educational activities with parents (*ped*) with educational activities with other adults (*oed*). This time input was also often ranked near the top in table A2. The Wald statistic for the *IU* test is again equal to zero for both the PPVT and MRT tests and for all estimators. But this time the statistic for the *EI* test is smaller and never significant. This is probably due to the relatively low variation in educational activities with other adults (see table 4), which causes the coefficient on *oed* to be imprecisely estimated.

Next, we extend our test by including time in before/after school care in our set of "inferior" time inputs (alongside time in general care with parents or other adults and time in bed). We refer to the rankings where educational time with parents or with other adults are the "superior" inputs as Rnk3 and Rnk4, respectively. These tests involve one additional inequality than the test in (3), so the Wald statistics can only be larger. The results for Rnk3 and Rnk4 are little changed from the previous results for Rnk1 and Rnk2: the Wald statistics for the inequality tests are zero or approximately zero, so we never reject the ranking. The equality test is rejected for educational activities with parents (the only exception being the FE estimates for the MRT score) but not for educational activities with other adults. Thus, the LSAC data suggest that one could improve children's cognitive test scores via a reallocation of time that increases time in educational activities with parents while reducing time in general care activities, in bed, or in before/after school care. This conclusion holds under all estimators.

Since the data back Rnk1 and Rnk3, we proceed to test the stronger hypothesis that educational activity with parents (*ped*) is more productive than time using the media (*mda*) and that time using the media is more productive than time in general care with parents or other adults and time in bed. We call this Rnk5. The hypothesis that time spent using media is among the most productive activities seems consistent with table A1 but less so with A2. Formally, the inequality test can be written as

$$\begin{gathered} H_2 :\ \beta_{aed} \geq \beta_{mda} \geq \{\beta_{pcr},\ \beta_{ocr},\ \beta_{bed}\} \\ \text{vs.} \\ H_1 :\ \{\beta_{ped},\ \beta_{mda},\ \beta_{pcr},\ \beta_{ocr},\ \beta_{bed}\} \in \mathbb{R}^5, \end{gathered} \tag{6}$$

while the equality test that is analogous to (5) follows accordingly. The test in (6) involves two more inequalities than the test in (3). Nevertheless, as we see in tables 14–15, we still obtain small Wald statistics, and the hypothesis of inequality is never rejected. At the same time, the hypothesis of equality is always strongly rejected. These results indicate that parents could improve cognitive outcomes by substituting media time for general care with parents or other adults and time in bed or, better yet, by increasing time in educational activities with parents.

Finally, we add one more inequality by adding time in before/after school care to the set of "inferior" inputs (i.e., time in general care with parents or other adults and time in bed). We call this Rnk6. By transitivity this also implies that educational activities with parents are the most productive activities. This time the null hypothesis holds for the PPVT test, but it is sometimes rejected for the MRT score. This is an interesting result: some parents may view having their child home using media as a normal alternative for before/after school care. The LSAC data indicate that this substitution might benefit the child's verbal skills (PPVT) but not logical skills (MRT).

E. Functional Form and Optimal Allocation

All our models specify a linear relationship between the time inputs and the children's skills. Thus, the results should be interpreted at the margin: that is, they measure the effect of reallocating children's time within the range of variation provided by the data. The effect would eventually break down for large reallocations because the marginal products cannot be constant, especially since time is a finite resource.

We checked the robustness of our results to functional form assumptions by reestimating all models in log form ($\ln Y_{ia} = TI'_{i\{K\times a\}}\beta_{\{K\times a\}} + PB'_{i\{G\times a\}}\delta_{\{G\times a\}} + e_{ia}$) and then replicating the ranking tests of tables 14–15. These results are reported in the appendix. The results are virtually unchanged.

We also tried to reestimate the models using a second degree polynomial in the time inputs ($Y_{ia} = TI'_{i\{K\times a\}}\beta_{\{K\times a\}} + TI^2_{i\{K\times a\}}{}'\varsigma_{\{K\times a\}} + PB'_{i\{G\times a\}}\delta_{\{G\times a\}} + e_{ia}$). However, the estimates become very imprecise and the adjusted R-squareds did not improve.

It is also important to recognize that, if parents are making input choices optimally, then our estimates imply nothing about it being optimal to have any change in behavior. While our study is informative about the productivity of each time input, optimal allocations also depend on input prices. Marginal products should not be expected to be equalized at the optimum. Our results are nevertheless of interest since incomplete information about the production function may cause suboptimal decisions for parents, in the way they allocate their children's time, and for policy makers, in the way they use levers at their disposal (e.g., child care subsidies, parental leave policies) to change the time input prices so as to enhance child development.

F. Model Uncertainty

When many models are initially considered, all of them defensible, the analyst has three main options. The first is to pick one model and adopt the conclusions that flow from it rather than from the other defensible models. But, as we explained earlier, we eschew any attempt to choose a "best" model, as any criterion we could use would necessarily be controversial. The second option is to present the analyses based on all the plausible models without choosing between them. This is the idea of sensitivity analysis, and it is our preferred option here. The third possibility is to take account explicitly of model uncertainty, for instance, through Bayesian Model Averaging (BMA). The logic of Bayesian inference says that one should obtain results from every model under consideration, average them, and then draw the conclusions from the averaged results. Suppose that we want to use the data D to compare competing hypotheses, which are represented by the S statistical models $M_1, \ldots, M_S$. Then, by Bayes's theorem, the posterior probability that M_s is the true model (given that one of the $M_1, \ldots, M_S$ models is the true one) is

$$p(M_s|D) = \frac{p(D|M_s)p(M_s)}{\sum_{\ell=1}^{S} p(D|M_\ell)p(M_\ell)}.$$

One can then use $p(M_s \mid D)$ to weight the model. We implement BMA following Raftery (1995) and Brock and Durlauf (2001). We put all the models on an equal footing a priori, so that $p(M_s) = 1/S \;\forall\; s$, where $S = 5$ in our case. We then approximate $p(D|M_s) \approx \exp[(1/2)BIC_s]$ where BIC is the Bayesian information criterion. Then

$$p(M_s|D) = \frac{\exp(-0.5BIC_s)}{\sum_{\ell=1}^{S}\exp(-0.5BIC_\ell)}.$$

Table 16 illustrates the results for the two cognitive skills. In both cases the posterior odds favor the Contemporaneous + Lagged Inputs + Lagged Test (CV) model strongly: the weight is 1. This would suggest using the estimates from the CV model alone.

While the ranking of time inputs is very similar across estimators, such that focusing on the CV model alone would not alter the main conclusions (only the FE estimator stands out on some occasions) we still take the BMA results with caution. BMA assumes that one of the models is the "true" one, something we cannot be sure of, as explained in Section III.F. Moreover, the implication of BMA is to focus on one set of (averaged) results rather than testing their sensitivity across different specifications. It is not clear to us that model averaging is a better way to deal with model uncertainty. We still believe that sensitivity analysis is more appropriate in our context.

G. Other Robustness Checks

In the appendix we present the Wald statistics obtained when using waves 3 and 2 rather than waves 2 and 1. The results point in a similar direction. Rnk1–Rnk6 *IU* tests are rarely rejected and the equality *EI* tests are often rejected for the PPVT score. In contrast to the tests in table 14, however, the *EI* tests now often fail to reject for the MRT score. Unfortunately, the smaller sample size adversely affects the power of the tests. This is particularly true when using the CU and CV estimators for which we have no more than 200 observations.

We also tried to impute some of the incomplete time slots using the where and with whom entries. We did so whenever there were only a handful of incomplete slots in the diary. While sample size increased there was no substantial change in the results. Therefore, we chose to present the results without the imputed time slots.

Table 16
Weights in Bayesian Model Averaging

	CT	VA	FE	CU	CV
PPVT:					
BIC	3.0321e+03	2.5076e+03	4.1671e+03	1.4066e+03	1.3204e+03
$p(M_s \mid D)$	0	0	0	0	1
MRT:					
BIC	3.1553e+03	2.7898e+03	4.1986e+03	1.4414e+03	1.4014e+03
$p(M_s \mid D)$	0	0	0	0	1

Finally, a referee suggested that we instrument for the lagged test scores in the value added models: VA and CV. This suggestion follows from the idea that test scores may measure innate ability with error. Instrumenting for the lagged test scores is straightforward in the case of the cognitive ability tests, since all we need is another test score that is correlated with the lagged one. In the case of the PPVT score, we use the Who Am I? test as an instrument for the lagged PPVT. In the case of the MRT score, we use the lagged PPVT as an instrument for the Who Am I? test. Using instrumental variables leads to larger estimates of the lagged test score coefficients, but more importantly it has little effect on the time use coefficients and the corresponding ranking tests. Finding instruments for the lagged noncognitive test scores is more difficult. Since these are derived from factor analysis they are orthogonal by construction. Therefore we were unable to implement IV for the behavioral test results.

H. Heterogeneity

In this section we explore whether the results are heterogeneous across subgroups. We report the results of the *IU* and *EI* tests only.

1. Child Gender

We first split our sample of children according to their gender. Table 17 reports the average number of hours in each activity by gender. Girls spend more time than boys in educational activities with parents and in bed. Boys spend more time using media. These differences are statistically significant at the 1% level. To test for heterogeneity in the production function across genders we reestimate all the models for boys and girls separately. Therefore, all the coefficients, and not just those on the time inputs, are allowed to vary across gender. Tables 18 and 19 report the Wald statistics for the input ranking tests, using the PPVT and MRT test scores, respectively.

For the PPVT test, there are no large differences between boys and girls, and the results are similar to those obtained using the whole sample (table 14). One exception is given by the small and rarely significant Wald statistics obtained when using fixed effects, where power is likely quite low given the small sample size.

For the MRT test, the results for girls are relatively close to those obtained when using the whole sample (table 15). But in the case of boys the

Table 17
Weekly Time Allocation by Gender (Wave 2 Only)

	ped	*pcr*	*sch*	*oed*	*ocr*	*soc*	*mda*	*bed*	*unk*
Boys	5.54	25.35	34.45	.11	1.36	15.62	9.38	75.88	.30
Girls	6.12	25.05	34.56	.16	1.25	15.49	8.08	77.00	.30

NOTE.—Numbers in tables are means. Observations: boys = 544; girls = 520.

Table 18
Ranking Test—PPVT—by Child Gender

	CT		VA		FE		CU		CV	
	IU	*EI*	*IU*	*EI*	*IU*	*EI*	*IU*	*EI*	*IU*	*EI*
Boys:										
Rnk1: *ped* > {*pcr*, *ocr*,*bed*}	.00	17.10**	.00	13.02**	.00	1.80	.00	5.48*	.00	6.97**
Rnk2: *oed* > {*pcr*, *ocr*,*bed*}	.00	3.60	.00	3.34	.00	2.99	.00	2.13	.00	1.87
Rnk3: *ped* > {*pcr*, *ocr*,*bed*,*sch*}	.00	17.29**	.00	13.42**	.00	3.85	.00	5.54	.00	7.01*
Rnk4: *oed* > {*pcr*, *ocr*,*bed*,*sch*}	.00	4.26	.00	3.76	.00	5.91	.00	2.20	.00	2.07
Rnk5: *ped* > *mda* > {*pcr*,*ocr*,*bed*}	.00	18.09**	.00	13.55**	.27	3.81	.00	6.84**	.00	9.84**
Rnk6: *ped* > *mda* > {*pcr*,*ocr*,*bed*, *sch*}	.00	18.21**	.00	13.89**	.27	9.10**	.00	6.88*	.00	9.85**
Girls:										
Rnk1: *ped* > {*pcr*, *ocr*,*bed*}	.00	8.40**	.00	11.98**	.98	2.57	.00	9.74**	.00	9.21**
Rnk2: *oed* > {*pcr*, *ocr*,*bed*}	.00	2.07	.00	3.34	1.10	3.07	.76	4.06	.00	2.04
Rnk3: *ped* > {*pcr*, *ocr*,*bed*,*sch*}	.00	11.87**	.00	19.30**	.99	4.07	.00	11.98**	.00	10.70**
Rnk4: *oed* > {*pcr*, *ocr*,*bed*,*sch*}	.00	5.24	.00	9.73**	1.11	3.53	.76	6.15	.00	3.04
Rnk5: *ped* > *mda* > {*pcr*,*ocr*,*bed*}	.00	9.59**	.00	12.39**	1.73	1.93	.01	10.90**	.00	9.68**
Rnk6: *ped* > *mda* > {*pcr*,*ocr*,*bed*, *sch*}	.00	14.47**	.00	21.55**	1.74	3.08	.01	14.04**	.00	11.66**

NOTE.—Numbers in table are Wald statistics. *IU*: inequality vs. unrestricted test. *EI*: equality vs. inequality test.
* Significant at the 10% level.
** Significant at the 5% level.

EI tests rarely reject when using the CU and CV estimators. This differs from the findings for girls or the whole sample. The implication of this is that the evidence that educational time with parents is superior to the other inputs is much weaker for boys than for girls. This pattern is not replicated when using the CT and VA estimators, however. We do not have a clear intuition to explain this difference based on gender. But, since the CU and CV estimators include the lagged time inputs, this result might suggest that boys are more sensitive than girls to early childhood investments.

2. *Mother's Education*

Next, we split the sample based on mother's education: (1) mothers who have completed at most a certificate degree versus (2) mothers with an

Table 19
Ranking Test—MRT—by Child Gender

	CT		VA		FE		CU		CV	
	IU	*EI*	*IU*	*EI*	*IU*	*EI*	*IU*	*EI*	*IU*	*EI*
Boys:										
Rnk1: *ped* > {*pcr*, *ocr*,*bed*}	.11	8.61**	.47	10.88**	.00	2.89	.14	1.96	1.22	3.32
Rnk2: *oed* > {*pcr*, *ocr*,*bed*}	.00	9.16**	.00	12.45**	.00	2.41	.00	2.34	.00	5.23*
Rnk3: *ped* > {*pcr*, *ocr*,*bed*,*sch*}	.65	15.13**	.71	16.52**	.00	2.96	.14	2.26	1.22	3.43
Rnk4: *oed* > {*pcr*, *ocr*,*bed*,*sch*}	.00	17.12**	.00	18.59**	.00	2.42	.00	2.72	.00	5.44
Rnk5: *ped* > *mda* > {*pcr*,*ocr*,*bed*}	.78	8.86**	.70	13.17**	.01	3.91	.55	1.81	2.03	3.33
Rnk6: *ped* > *mda* > {*pcr*,*ocr*,*bed*, *sch*}	2.35	13.23**	1.37	17.43**	.01	4.17	.55	2.02	2.03	3.39
Girls:										
Rnk1: *ped* > {*pcr*, *ocr*,*bed*}	.00	8.99**	.00	9.20**	.54	.86	.00	15.37**	.00	12.72**
Rnk2: *oed* > {*pcr*, *ocr*,*bed*}	.00	.46	.00	4.30	.01	1.87	.35	2.73	1.47	1.94
Rnk3: *ped* > {*pcr*, *ocr*,*bed*,*sch*}	.00	16.79**	.00	12.35**	.65	1.01	.00	16.82**	.00	14.37**
Rnk4: *oed* > {*pcr*, *ocr*,*bed*,*sch*}	.00	9.81**	.00	8.44*	.01	2.36	.48	5.58	1.84	4.96
Rnk5: *ped* > *mda* > {*pcr*,*ocr*,*bed*}	.00	9.09**	.00	11.75**	.53	.91	.00	15.48**	.00	12.91**
Rnk6: *ped* > *mda* > {*pcr*,*ocr*,*bed*, *sch*}	3.40	12.67**	.04	13.74**	.62	1.20	1.18	16.10**	1.12	14.20**

NOTE.—Numbers in table are Wald statistics. *IU*: inequality vs. unrestricted test. *EI*: equality vs. inequality test.
* Significant at the 10% level.
** Significant at the 5% level.

advanced degree or above.[15] While the full sample results imply that time in educational activities with parents is beneficial for cognitive development, it is possible that this is only true for more highly educated mothers. Intuitively, the more educated the mother, the better the "quality" of her time. But on the other hand, more educated mothers might also ensure better quality substitutes for maternal time.

[15] Table 7 in Sec. II.B describes the distribution of mother's education. In the Australian education system an advanced degree requires the completion of year 12, and it is classified just below a bachelor's degree. We do not split the sample into more than the two subgroups because the sample size of some subgroups would be very small.

The statistics in table 20 show that children with more educated mothers spend more time in educational activities with parents and more time in social activities. On the other hand, they spend 1.6 fewer hours per week using media. These differences highlight the importance of controlling for parental education in order to obtain consistent estimates of the effect of time inputs.

Table 21 illustrates the results for the PPVT test score. For both high and low education mothers we find evidence that time in educational activities with parents is more productive than other time inputs. But the evidence is weaker for the less educated mothers. That is, in the top panel of table 21 there are a few cases where the *EI* test does not reject equality of the time inputs coefficients.

In the case of the MRT test, table 22, we do not find much difference by education. The overall pattern of educational activities with parents being better than media, which in turn is better than the other activities, generally holds regardless of the mother's education. In summary, we find evidence that educational time with parents is superior to other time inputs for both the PPVT and the MRT. But the evidence from the MRT is more clear.

V. Conclusion

The aim of this study is to investigate the determinants of child cognitive and noncognitive development using a much richer specification of the production function than in prior work. Rather than examining the effects of only one or two time inputs at the time—as has been common—we attempt to look at all the child's activities within a representative week. By doing so we characterize the trade-off between all alternative activities to which a child is exposed. This richer specification of inputs is made possible by the LSAC diary data whose purpose is to collect a detailed record of all of a child's activities in a week as well as collecting a rich set of measures of other inputs to child development.

A few important conclusions can be drawn from the findings of this study. One key result is that cognitive skills are affected by the way children's time is allocated. Educational activities such as reading a story, being talked to, or helping with chores are the most "productive," particu-

Table 20
Weekly Time Allocation by Mother's Education (Wave 2 Only)

	ped	*pcr*	*sch*	*oed*	*ocr*	*soc*	*mda*	*bed*	*unk*
No HE	5.52	25.43	34.35	.14	1.28	15.06	9.40	76.46	.34
HE	6.22	24.85	34.72	.13	1.35	16.30	7.79	76.41	.24

NOTE.—Numbers in tables are means. Observations: No HE = 608; HE = 449. HE = higher education.

Table 21
Ranking Test—PPVT—by Mother's Education

	CT		VA		FE		CU		CV	
	IU	*EI*	*IU*	*EI*	*IU*	*EI*	*IU*	*EI*	*IU*	*EI*
No higher education:										
Rnk1: *ped* > {*pcr*, *ocr*,*bed*}	.00	11.83**	.00	7.32**	.17	1.84	.00	3.91	.00	5.71*
Rnk2: *oed* > {*pcr*, *ocr*,*bed*}	.00	1.65	.00	.22	.16	1.58	.00	1.87	.00	4.75
Rnk3: *ped* > {*pcr*, *ocr*,*bed*,*sch*}	.00	13.71**	.00	13.23**	.18	2.29	.00	5.34	.00	5.73
Rnk4: *oed* > {*pcr*, *ocr*,*bed*,*sch*}	.00	3.36	.00	6.01	.18	1.88	.00	3.46	.00	4.88
Rnk5: *ped* > *mda* > {*pcr*,*ocr*,*bed*}	.00	11.83**	.00	7.48**	.36	1.44	.11	3.87	.00	5.71*
Rnk6: *ped* > *mda* > {*pcr*,*ocr*,*bed*, *sch*}	.00	13.73**	.00	14.01**	.37	1.83	.12	5.21	.00	5.73
Higher education:										
Rnk1: *ped* > {*pcr*, *ocr*,*bed*}	.00	10.09**	.00	12.89**	.00	1.74	.00	6.58**	.00	5.29*
Rnk2: *oed* > {*pcr*, *ocr*,*bed*}	.00	2.79	.00	2.37	.00	3.70	.00	1.29	.19	.26
Rnk3: *ped* > {*pcr*, *ocr*,*bed*,*sch*}	.00	10.13**	.00	12.94**	.00	6.23*	.00	6.60*	.00	5.29
Rnk4: *oed* > {*pcr*, *ocr*,*bed*,*sch*}	.00	2.80	.00	2.41	.00	5.42	.00	1.31	.20	.34
Rnk5: *ped* > *mda* > {*pcr*,*ocr*,*bed*}	.00	18.94**	.00	17.60**	1.04	2.76	.00	9.78**	.00	7.38**
Rnk6: *ped* > *mda* > {*pcr*,*ocr*,*bed*, *sch*}	.00	20.06**	.00	17.64**	1.04	9.97**	.00	9.86**	.00	7.50*

NOTE.—Numbers in table are Wald statistics. *IU*: inequality vs. unrestricted test. *EI*: equality vs. inequality test.
* Significant at the 10% level.
** Significant at the 5% level.

larly when they are done with the parents. A reallocation of children's time that favors this kind of activity by substituting away from time in general care, bed, or before/after school care would have a positive effect on skills. The effect is estimated to be quantitatively large, comparable to the effect of increasing parental education. This result is robust to different identification assumptions—that is, it holds for all five major approaches to estimating the skills production function discussed by Todd and Wolpin (2003, 2007).

Perhaps more surprisingly, time spent using media such as TV and computers does not seem necessarily detrimental to development. For example, for reading skills, it is at least as productive as time in before/after

Table 22
Ranking Test—MRT—by Mother's Education

	CT		VA		FE		CU		CV	
	IU	*EI*	*IU*	*EI*	*IU*	*EI*	*IU*	*EI*	*IU*	*EI*
No higher education:										
Rnk1: *ped* > {*pcr*,*ocr*,*bed*}	.00	10.45**	.00	7.78**	.00	6.58**	.00	9.89**	.00	7.97**
Rnk2: *oed* > {*pcr*,*ocr*,*bed*}	.00	2.56	.00	3.12	.00	4.88	.64	2.44	2.78*	2.01
Rnk3: *ped* > {*pcr*, *ocr*,*bed*,*sch*}	.00	16.12**	.00	8.50**	.00	6.67*	.00	9.96**	.00	8.06**
Rnk4: *oed* > {*pcr*, *ocr*,*bed*,*sch*}	.00	9.18**	.00	3.98	.00	4.91	.66	2.44	2.83*	2.01
Rnk5: *ped* > *mda* > {*pcr*,*ocr*,*bed*}	.19	10.38**	.00	8.55**	.00	7.03**	1.31	8.23**	.60	7.80**
Rnk6: *ped* > *mda* > {*pcr*,*ocr*,*bed*, *sch*}	3.19	12.29**	.00	9.16**	.00	7.37*	1.32	8.33**	.60	7.88**
Higher education:										
Rnk1: *ped* > {*pcr*,*ocr*,*bed*}	.00	5.24*	.00	5.08*	.54	3.25	.00	4.29	.00	3.02
Rnk2: *oed* > {*pcr*,*ocr*,*bed*}	.00	6.77*	.00	5.15	.46	3.69	.86	.09	2.44*	.23
Rnk3: *ped* > {*pcr*, *ocr*,*bed*,*sch*}	.55	13.13**	.76	14.72**	.61	3.28	.01	10.78**	.03	7.86**
Rnk4: *oed* > {*pcr*, *ocr*,*bed*,*sch*}	.00	17.30**	.00	17.15**	.46	3.89	1.17	6.65	2.79*	5.71
Rnk5: *ped* > *mda* > {*pcr*,*ocr*,*bed*}	.00	7.97**	.00	9.52**	1.89	3.71	.00	5.30*	.00	4.98*
Rnk6: *ped* > *mda* > {*pcr*,*ocr*,*bed*, *sch*}	1.27	13.15**	1.24	16.12**	1.89	3.78	2.86	9.22**	1.30	7.99**

NOTE.—Numbers in table are Wald statistics. *IU*: inequality vs. unrestricted test. *EI*: equality vs. inequality test.
* Significant at the 10% level.
** Significant at the 5% level.

school care.[16] We stress that our estimates of the productivity of inputs hold "at the margin," since we use a linear approximation to the production technology and our data vary in a limited range. Obviously one would not want to extrapolate the results beyond the range of variation in the data.

[16] Although we find that time using the media can be productive, we do not know what kind of TV or computer program the children use. The data only tell us how much time is spent on it but not what they do with the media. Still, these results indicate that the effect of media is an important area of research. There are a few recent papers that look at the effect of being exposed to media. See, e.g., Gentzkow and Shapiro (2008), Fiorini (2010), Vigdor and Ladd (2010), and Malamud and Pop-Eleches (2011). However, these papers have little or no information on the content of the media.

When breaking the sample into subgroups we find that there are differences in the way time is allocated for boys and girls. Girls spend more time than boys in educational activities with parents and also in bed. Boys spend more time using media. Also, our results on educational activities with parents being superior to other inputs are more robust for girls than for boys.

The data also show that children with more educated mothers spend more time in educational activities with parents and in social activities. On the other hand, they spend about 1.6 hours less per week using media. We find some evidence that time in educational activities has a larger positive effect on reading skills if the mother is more educated, but the evidence is quite weak. Thus, the superiority of educational time with parents over other inputs appears to hold even for less educated mothers.

Another key finding is that the production functions for cognitive and noncognitive skills are very different. With respect to noncognitive skills like behavioral problems, social skills, and emotional problems, the allocation of children's time is not important. Instead we find that these skills are strongly influenced by parenting style, particularly mother's warmth and effective discipline. A parenting style that combines effective (but not harsh) discipline with parental warmth and affection leads to the best behavioral outcomes. Either leniency or excessive harshness in discipline lead to worse outcomes.

In discussing the determinants of child development, it is useful to compare our results with previous studies in the fields of developmental psychology, education, medical science, and sociology.[17] However, we could not find a comparable time use study where activities are ranked and the trade-offs are made explicit. Thus, our study seems rather novel in its approach, making comparisons difficult. We are certainly not the first to stress the importance of parental time. But our study highlights that it is difficult to find an equally beneficial substitute. Similarly, the literature is devoting a growing amount of attention to the role of media, but there is little discussion of the trade-off between media and alternative inputs.[18]

The noneconomics literature has also long stressed the link between parenting style on the one side and cognitive and noncognitive development on the other. Our paper shows that the evidence of a link with noncognitive skills is robust to a range of estimators commonly used in econometrics. However, we do not find evidence of any link with cognitive skills. We suspect that part of the explanation may be the measurement of parenting style. In our data, information on parenting is limited to traits that we label maternal warmth and discipline. This is consistent with classic, early studies

[17] Shonkoff, Phillips, and National Research Council (2000) offers an extensive review of the research approaches and findings in those fields.

[18] See, e.g., Subrahmanyam et al. (2001) and Schmidt and Anderson (2007).

of child rearing that sought to identify styles of parenting that promoted competent behavior in preschoolers (i.e., a child who is happy, self-reliant, self-controlled, friendly, and cooperative as distinct from withdrawn or immature).[19] Nevertheless, part of this literature has more recently extended the analysis to traits like contingency, reciprocity, and restrictiveness that have been found to matter for cognitive skills, but for which we have no direct measure.[20]

Our findings suggest the importance of further research in a number of areas. First, the literature on child development can benefit from collecting and analyzing time use data. Our results indicate that these time inputs can be just as important as the parental background characteristics and goods inputs that have received most of the attention in prior work. Second, the trade-off between inputs, whether these are time allocations or goods, is often overlooked. As a consequence, some studies might convey limited and potentially misleading information. When possible, more emphasis should be placed on such trade-offs. Third, the effect of time using media on child development deserves further consideration. While children are increasingly exposed to a variety of media, little is known about how different media and their content affect child development—at least not relative to other inputs. Our findings, together with previous studies, indicate that media can be an important input in the production function. Finally, the role of parenting style has also received scant attention in economics. However, our results combined with earlier research in developmental psychology indicate that it is of substantial importance, at least for noncognitive skills.

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[19] See the seminal paper by Baumrind (1966).
[20] See, e.g., Landry et al. (1997).

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