Evaluating the Effect of Maternal Time on Child Development Using the Generalized Propensity Score

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Mainly due to data unavailability, time with the mother is usually not considered in empirical papers trying to find the determinants of child's achievement. We attempt to do so in this paper by using the Child Development Supplement of the Panel Study of Income Dynamics (PSID). This Supplement surveys PSID participants' children and, important to our purpose, it collects a child's time-use diary, which allows us to compute the number of hours each child spends with the mother and in school/care during a typical day. Furthermore, the Supplement implements standard tests to children providing therefore cognitive and non cognitive test scores. With this information we can assess the effect that the time spent with the mother and in school/care may have on children's cognitive and non cognitive achievement, controlling for a bunch of child's, mother's, family's and environmental characteristics. To do so, we implement the methodology developed recently on the program evaluation of continuous treatments. We divide our full sample of 1497 children in two age groups (young and old) and two race groups (black and white). We find that more time with mothers and less time in school/care leads both young and old children to perform better in cognitive tests. When we divide our sample according to race we find that young black children tend to perform worse if they spend more than 5 hours with the mother in a day. Accordingly this sub sample seems to benefit from spending more time in school/care. For white children we find the opposite effect: they tend to perform better if the time spent with mothers increases and the time in school/care decreases. Also these effects tend to occur until later ages for white children.

Keywords: word; Maternal time, Cognitive and non-cognitive outcomes, Treatment evaluation.

JEL codes: C21, I29.

1 Introduction

There is evidence from psychology, neuropsychology and other sciences that the time the child spends with the primary caregiver (usually the mother) is essential for her cognitive, social and emotional development. Neuropsychological research on attachment theory finds that the interaction between the primary caregiver and infant stimulates brain development (Shore (1997)). Also, the economics literature acknowledges the importance of childhood in the later outcomes. Carneiro et al. (2003) and Cunha et al. (2006) find that cognitive and non-cognitive skills are strongly influenced by parental behaviour and abilities, suggesting that economic success is already partly determined in early childhood.

Therefore the experiences the child has during childhood may determine future success in life. This paper tries to understand to what extent the time that children spend with their mother affect indeed their cognitive and non-cognitive development. Several papers in the economic literature attempt to determine the determinants of child's output from cognitive and non-cognitive test scores. There are not many papers that include the time mother and child spend together as an explanatory variable mainly due to data unavailability. The best some papers do is to relate maternal employment (in intensive and extensive margin) to child outcomes, i.e. they assume that the mother's non-working time is entirely spent with the child (e.g. Bernal and Keane (2005), James-Burdumy (2005), Blau and Grossberg (1992), Ruhm (2004)). The above methodology, despite being very interesting, only allows to assess the impact of working status (or working hours) on test scores while it does not allow to make any considerations about the impact of the actual time they spend together. We can think of two cases in which the former analysis would lead to wrong conclusions: i) mothers that don't work or do work very few hours but spend very few of their free time with children; and ii) mothers that do work or work for longer hours but that spend almost their entire free time with their children. So, if one attempts to relate mother-child time with child outcomes it is important to have a direct measure of the actual time they spend together. The type of data needed to do such an analysis is very hard to find because we must have simultaneously child outcomes and an accurate measure of time. The usual time diary surveys do not have the former while other databases do not have the later. In this paper we use a unique data set from the 1997 PSID - Child Development Supplement made with the purpose of providing researchers with a comprehensive database of children and families that would enable to study the dynamic process of early human capital formation. Up to 2 children per PSID family aged 0-12 years during the calendar year of 1997 were selected for interview. The interview included a time use diary with 24-hour detailed accounting of time use for one randomly selected weekday and weekend, with the type, duration and location of activities and social context of activities (detailed information about whom participated in the activity and who else was there but not directly engaged). It was also collected aptitude and achievement test scores (reading and math and memory) and psychological, emotional and social well being (behaviour problem index, positive behaviour) as well as a bunch of family context variables. So this seems the perfect data set to assess the impact of mother-child time on child's test scores, as we have the two necessary variables and a bunch of variables to control for. We focus on three outcomes: letter word identification, applied problems and behaviour problem index. Our sample has 1497 children, which we then divide into two six sub-samples according to their age and race.

In order to assess the causal effect of the time spent with mothers in the cognitive and non cognitive achievement we use the recent development in program evaluation made by Hirano and Imbens (2004). The latter extends the usual binary treatment case to a continuous treatment, which suits particularly well our needs since the treatment variable we consider, time, is continuous. We are able then to use the generalized propensity scores and estimate dose response functions, i.e. the response function of each outcome to each level of the treatment variable.

The remainder of the paper is organized as follows. Next section describes the use of the generalized propensity score and methodology of estimating a dose response function to evaluate a continuous treatment. Section 3 presents the data used in this paper. The fourth section presents our empirical results and section 5 concludes.

2 The generalized propensity score

In recent years the research in program evaluation has made comprehensive use of matching methods. The standard case considers a binary treatment. Rosenbaum and Rubin (1983) provided the key result that has made the matching such an attractive method: rather than conditioning on the full set of covariates, conditioning on the propensity score, i.e. on the probability of receiving the treatment given the covariates, is sufficient to balance treatment and comparison groups.

More recently, the literature has extended propensity score methods to the cases of multi-valued treatments (Imbens(2000) and Lechner (1999)) and continuous treatments Hirano and Imbens (2004). The approach of the latter paper is particularly suitable for our purpose because it enables to estimate the entire dose response function of our continuous treatment-time. Therefore we follow closely Hirano and Imbens's (2004) methodology and implementation, that are summarized below.

2.1 Methodology

We have a random sample of units i=1,...,N and for each we observe a set of potential outputs $Y_i(t)$ from a treatment t. In the usual binary case the treatment set is $\breve{T} = \{0,1\}$

whereas in the continuous case $\breve{T}$ is an interval $[t_0, t_1]$. For each sample unit i we observe a vector of covariates X_i, the level of treatment actually received $T_i \in [t_0, t_1]$ and the outcome $Y_i(T_i)$. Our objective is to estimate the average dose response function $\mu(t) = E[Y(t)]$. In the remainder of the section we ignore subscript i.

The key assumption of Hirano and Imbens (2004) generalizes the unconfoundedness assumption for binary treatments to the continuous case. The weak unconfoundedness assumption is the following:

$$Y(t) \perp T \mid X, \forall t \in \breve{T} \tag{1}$$

and it is named so because it only requires independence to hold for each level of treatment t rather than the joint independence of all potential outcomes.

Call $r(t,x) = f_{T|X}(t,x)$, i.e. $r(t,x)$ is the conditional density of the treatment given the covariates. The generalized propensity score (GPS) is defined as:

$$R = r(T, X). \tag{2}$$

The GPS has a balancing property similar to that of the standard propensity score, as within the strata with the same value of $r(t,x)$ the probability of $T = t$ does not depend on the value of X. In other words, GPS has the following property:

$$X \perp 1\{T = t\} \mid r(t,x). \tag{3}$$

Hirano and Imbens (2004) highlight that this property does not require unconfoundedness. However, when combined with unconfoundedness, it implies that assignment to treatment is unconfounded given the GPS:

$$Y(t) \perp T \mid X, \forall t \in \breve{T} \Rightarrow Y(t) \perp T \mid r(T, X), \forall t \in \breve{T}. \tag{4}$$

Given this result it is possible to use the GPS to remove the bias associated with differences in covariates in two steps. First, estimate the conditional expectation of the outcome as a function of two variables- treatment T and GPS R:

$$\beta(t,r) = E[Y \mid T = t, R = r]. \tag{5}$$

Then we estimate the dose response function (DRF) at each particular level of the treatment. This is implemented by averaging the conditional expectation over the GPS at that particular level of treatment:

$$\mu(t) = E[\beta(t, r(t, X))]. \tag{6}$$

Notice that we do not average over the GPS $R = r(T, x)$ but instead we average over the score evaluated at the treatment level of interest $r(t,x)$.

It should be stressed that the regression function $\beta(t,r)$ does not a causal interpretation but $\mu(t)$ corresponds to the value of the DRF for treatment level t, which compared to another treatment level t′ does have a causal interpretation.

2.2 Implementation

In the practical implementation of the methodology outlined in the previous section we use a normal distribution for the treatment given the covariates:

$$T_i \mid X_i \sim N\left(\beta_0 + \beta_1' X_i, \sigma^2\right). \tag{7}$$

1. In the first stage we estimate the parameters β_0, β_1 and σ² by OLS. Then the estimated GPS is:

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp\left\{-\frac{\left(T_i - \hat{\beta}_0 + \hat{\beta}_1' X_i\right)^2}{2\hat{\sigma}}\right\} \tag{8}$$

2. In the second stage we model the conditional expectation of Y_i given T_i and R_i as a flexible function of its two arguments. In the application used by Hirano and Imbens (2004) a quadratic approximation is used:

$$E[Y_i \mid T_i, R_i] = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 R_i + \alpha_4 R_i^2 + \alpha_5 T_i R_i \tag{9}$$

   The parameters are estimated by OLS using the estimated GPS $\hat{R}_i$.

3. In the third stage, and given the estimated parameters in the second stage, the average potential outcome at treatment level t is estimated:

$$E\left[\hat{Y}(t)\right] = \frac{1}{N}\sum_{i=1}^{n}\left[\hat{\alpha}_0 + \hat{\alpha}_1 t + \hat{\alpha}_2 t^2 + \hat{\alpha}_3 \hat{r}(t, X_i) + \hat{\alpha}_4 \hat{r}(t, X_i)^2 + \hat{\alpha}_5 t\hat{r}(t, X_i)\right] \tag{10}$$

   We should do this for every treatment level we are interested in order to obtain the entire dose-response function. It is convenient to use bootstrap methods to form standard errors and confidence intervals.

3 Data

In this paper we use the Child Development Supplement (CDS) of the Panel of Income Dynamics (PSID). The PSID is a nationally representative sample of U.S. families that collects data on income, work and consumption. PSID families have been interviewed since 1968 and sample members are followed as they split off into new households. In 1997, with the purpose of providing researchers with a comprehensive database of children and families that would enable to study the dynamic process of early human capital formation, it was developed the PSID Child Development Supplement. Up to 2 children per PSID family aged 0-12 years during the calendar year of 1997 were selected and interviewed. The interview included a time use diary with 24-hour detailed accounting of time use for one randomly selected weekday and weekend, with the type, duration and location of activities and social context of activities (detailed information about whom participated in the activity and who else was there but not directly engaged). It was also collected aptitude and achievement test scores (reading and math and memory) and psychological, emotional and social well being (behaviour problem index, positive behaviour) as well as a bunch of family context variables. So this seems the perfect data set to assess the impact of mother-child time on child's test scores.

For each individual in our sample we compute the total time they spend with mothers in a week day[1]. This variable englobes the time that the mother is participating in the activity with the child or not, i.e. the mother might just be around while the child does an activity by herself. Furthermore, we also consider the time spent in the major alternative to maternal time, i.e. time spent in school or in any form of child care. So, we have two treatment variables and we will analyze the effect that these treatments have on child's outcomes. We are particular interested in three outcomes: i) Letter-Word Identification (LW), that measures child's reading skills; ii) Applied Problems (AP), that measures child's mathematical skills; and iii) Behaviour Problem Index (BPI), which is a measure of the child's behaviour problems. So we have information both on cognitive (LW and AP) and non-cognitive (BPI) skills. Table 1 in the appendix describes all the variables we use in our analysis.

In 1997, 3563 children were interviewed. We will only consider the 2478 children that completed the time diary questionnaire (both in week and weekend days), that live with the mother and for whom their mother was reported to be the primary caregiver. Our final sample consists of 1497 children that have available at least one of our three outcome variables and for whom none of the several covariates we consider (child's, mother's and family's characteristics) is missing. In the forthcoming analysis we always divide children in two age groups: the first group is composed by younger children (from 3 to 6 years old) and is named Young and the second group is composed by older children (from 7 to 12 years old) and is named Old. We believe it is important to make this distinction because the time needs for one and other group seem to be very different and can therefore affect determinately the impact of the treatment. Furthermore, later on in the paper, we distinguish between white and black children because the majority of their covariates is significantly different from each other. We see this by computing the difference in means and checking whether these are significantly different from zero. We conclude that, both for young and old children, the means of the following covariates are significantly different between races: birth weight, age breast feeding stopped, mother's age at birth, marital status at birth, mother's education, dummy for both parents living with the child,

[1] For now we focus on a week day as these are the days in which a time constraint is more relevant. Later on we intend to use also the weekend time diary and see whether there is any time compensation during the weekend.

dummy of other adults living in house, dummy of living at own house, father's education, 5 year average of total income, mother's fixed effect and state's average weekly wage.

So, summarizing we have 6 different samples: young children with 561 observations, old children with 936 observations, young white children with 341 observations, young black children with 220 observations, old white children with 540 observations and old black children with 396 observations. We implement the methodology presented in the previous section separately for each of them. Table 2 presents the summary statistics for every variable we use and for each of the six samples.

On average mothers with young children spend more hours in a week day with children than mothers with old children. In this table we present the standard outcomes but in all our analysis we normalize them to have mean 0 and standard deviation 1 within each sample. Young children perform worse than old children in LW, AP and better in BPI. Analyzing the columns corresponding to the division of children according to age and race (columns (3) to (12)) we conclude that white children perform much better in all outcomes considered. Also, white mothers spend more than 1 hour per week day with their children irrespectively of being young or old. This could lead us to think that indeed time with mothers determines the outcomes as we observe an association between higher treatments and higher outcomes. However, notice that there exists selection bias, i.e. we observe that the characteristics of black and white samples are very different and significant as explained above. Furthermore the black samples seem to be disadvantaged in comparison with their white counterparts in almost every characteristics we can observe: white children weighted more at birth, were breast fed longer, had an older mother at birth, have more educated mothers and fathers, are more likely to be part of a bi-parental family, have less siblings, are more likely to own their house, belong to richer families, and have abler mothers. So, indeed white children seem to have a privileged background and it may make sense to analyze race separated samples to see to what extent the effect of maternal and school/care time on child development is different.

4 Results

4.1 GPS, Covariance Balance and Common Support

We first estimate the conditional distribution of the treatment by estimating equation (7) by OLS. Then we compute the GPS according to equation (8). As in the binary treatment case it is important to impose common support. This guarantees that for the same propensity score there are observations from the different treatment groups and therefore they can be compared. This may mean that some observations are dropped because they lie outside the common support. In our case, and depending on the subsample considered, we drop between 1 and 4.5 percent of our observations.

It is also important to evaluate how well the adjustment for the GPS works in balancing the covariates, i.e. if the specification of equation (7) is adequate. Even though in the continuous treatment case the procedure is more complicated, the idea is the same of the binary case: we test, before and after matching, for the equality of means of the covariates for the treated and control groups. As the original sample is imbalanced we expect to reject these tests before matching. However, if the adjustment for the GPS properly balances the covariates, we expect the differences in means not to be statistically different from zero. For our sample, and in all subsamples considered, we conclude that indeed this is the case, so we are confident in the appropriateness of our matching methodology.

4.2 Estimating and plotting the dose response functions

The final step is to estimate the GPS-adjusted dose response function and then we use these estimates to estimate equation (10), i.e. we estimate the expected outcome from each level of treatment. As young and old children are in different stages of their lives, they obviously make different use of time. Therefore the intervals for which we evaluate equation (10) are different. For young children, the maternal time lies between 0 and 12 hours per week day and the school/care time lies between 0 and 10 hours per week day. For old children the intervals are 0 to 8 hours per week day and 6 to 10 hours per week day, respectively.

4.2.1 Sample divided by age

Figure 1 presents the dose response functions of LW, AP and BPI for young and old children. Notice that these figures show the results of equation (10), i.e. the expected average outcome for each level of treatment we have considered. Both for young and old children, the LW and AP d.r.f. are clearly increasing in maternal time and decreasing in school/care time. This means that spending more hours per week day with the mothers lead children to perform better in these tests while the opposite occurs for time spent in school/care. The BPI d.r.f. is flatter both for young and old children, suggesting that spending more time with the mother or in school /care does not have an important impact on the behaviour score.

Notice that these graphs allow us to compare the estimated d.r.f. for the different levels of treatment but do not give any information on whether the differences are significant. For instance, for young children, we can tell that spending 12 hours per day with the mother is clearly better for LW score than don’t spending any time at all. However we can not tell whether it is significantly better, in statistical terms. To give some insight about the significance of these differences we evaluate the d.r.f. in 5 treatment levels[2], compute the difference between them and test whether these differences are indeed significant. The results of this procedure are presented in table 3. In each cell of the table we present the difference between the d.r.f. of the treatment in the row and in the column. For instance in the first cell (top left cell), the figure 0.02 means that, on average, we expect a difference of 0.02 in the LW scores between a child that spends 3 hours per day with the mother and a child that spends no time at all with the mother. However this difference is not significantly different from zero.

Analyzing table 3, and regarding the effect of maternal time on cognitive outcomes, we can see that the values for LW and AP are almost all positive for both young and old children. For school/care time the values are negative. This confirms that indeed the d.r.f. is increasing in maternal time and decreasing in school/care time. Several values are indeed significant and it is worthwhile to mention the magnitude of these differences, as they reach almost two fifths of a standard deviation. In both young and old samples none of the treatment variables seem to affect significantly the BPI outcome. Indeed the values in table 3 are very small and none is significant, which again suggests that the treatment does not have an impact on children behaviour.

4.2.2 Sample divided by age and race

By looking at all children in the same age group together we may be missing some important heterogeneous effect between children that are different along other dimensions, as for instance race. In table 2 it is evident that black children come from very disadvantaged backgrounds when compared to white children, therefore they may respond differently to each of the treatment variables. In this subsection we apply the same methodology used before to the sample divided not only by age but also by race. Interestingly the d.r.f. present very different patterns when we take each race separately.

Analyzing figure 2 it seems that the LW and AP d.r.f. of young white children are increasing in maternal time and decreasing in school/care time. This pattern is confirmed in table 7, in which we present the differences of the d.r.f. between several treatment variables: for maternal time, almost all the values for the white sample are positive and are particularly significant for LW; it seems to be positive to spend some time in school/care, but as this increases the effect become negative. The black young sample presents very different results. For maternal time, the LW and AP d.r.f. increase for smaller levels of treatment but then

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[2] For young children the levels of treatment considered are:

- For maternal time: 0, 3, 6, 9 and 12 hours per week day
- For school/care time: 0, 2.5, 5, 7.5 and 10 hours per week day

For old children the levels of treatment considered are:

- For maternal time: 0, 2, 4, 6 and 8 hours per week day
- For school/care time: 6, 7, 8, 9 and 10 hours per week day

decrease sharply for high levels of treatment, emerging a peak around the 5 hours per week day. The school/care time seems to increase LW score, while for AP the d.r.f. is rather flat. Indeed in table 4 all the significant values for maternal time are negative while for school/care time are positive. The BPI d.r.f. is rather flat for young white children and for black children there is no clear pattern. This suggests that, at least for cognitive outcomes, young white children seem to benefit particularly from maternal time, while black young children seem to benefit particularly from school/care time.

For older children the results seem to be qualitatively the same even though less pronounced at least for the black sample. Figure 3 suggests that old white children present higher cognitive scores the higher is maternal care and the lower is school/care time. Indeed, in table 5, the significant values are positive for maternal care and negative for school/care time. For black old children the results are smaller and less precise. The only significant value suggests that more time in school/care increases LW score. For BPI again the results are very small and there is no significant difference between spending more or less time with the mother or in school/care.

5 Conclusion

In this paper we use unique data from the PSID that collects a diary on children's time use and test scores. This data allows to measure the time that children spend with mothers and in school during a week day and to assess the importance that these times have on child's cognitive and non-cognitive test scores. We use the propensity score matching methodology applied for continuous treatments, as our treatment variables, time, are continuous. This methodology eliminates the selection bias problem and ensures that we find a causal effect between time with mothers and in school and test scores.

We conclude that more time with mothers leads both young and old children to perform better in cognitive tests. In contrast, more time in school/care is associated with lower cognitive scores. Once we divide our sample according to race and age we find that young black children tend to perform worse in those tests if they spend more than 5 hours in a day with mothers, but benefit from spending more time in school. The results for young white children are the opposite: their cognitive scores tend to increase with maternal time and decrease if school/care time is sufficiently high. For old black children we find no relation between time with mothers or in school and test scores, while for old white children the positive effect of time with mothers still persists. So we conclude that white children always benefit from time spent with mothers in a week day and benefit until later ages. It seems that black children tend to benefit particularly from the time spent in school/care while white children benefit particularly from time spent with mothers. This difference is certainly due to the fact that, in our sample, the black children are from very disadvantaged backgrounds when compared with their white counterparts. Probably, the quality of school relative to the quality of maternal care is higher for black than for white. This is a hypothesis we would like to explore in the future.

TABLES and FIGURES

Table 1. List of the variables used and their description

Variable Name	Definition
Outcomes	
LW	Letter- Word Identification (reading skills)
AP	Applied Problems (mathematical skills)
BPI	Behaviour Problem Index
Treatments	
Maternal Time	Hours child spends with mother in a week day
School/Care Time	Hours child spends in school or in care in a week day
Covariates	
Ageatpcg	Child's age at caregiver interview (months)
RaceWhite	Race - White (=1 if yes)
RaceBlack	Race - Black (=1 if yes)
Chgender	Child's gender (=1 if male)
Birthorder	Birth order from mother
Birthweight	Birth weight
Ageatbreast	Age breastfeeding stopped (months)
AgeBirthM	Mother's age at birth
MaritalBirth	Mother's marital status at birth (=1 if married)
EducationM	Mother's years of education
ParentLive	Both parents living (=1 if yes)
ChildrenFU	Number children in household
AgeYoungest	Age youngest child in the household
OtherAdults	Number of other adults (excluding mother)
OwnHouse	Family own house (=1 if yes)
EducationF	Spouse years of education
Avg(Total Income)	5 year average of total income in previous year (log, real terms)
Mother's FE[3]	Mother's fixed effect
AvgWeeklyWage	State's average weekly wage

[3] We compute the Mother's FE as follows. We have information on the wage the mother receives every 2 years from 1990 until 2003, so approximately 7 years before after the CDS data collection point. Furthermore we can compute the age of the mother at each of these data points. We build a panel with the wage, the age and the age squared and run a fixed effect model (xtreg wage age age², fe).

Table 2. Descriptive statistics by subsample

	Young		Old		Young Black		Young White		Old Black		Old White	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Treatments												
Maternal time	5.99	3.23	4.29	2.5	5.28	2.91	6.46	3.45	4.11	2.46	4.42	2.52
School/care time												
Outcomes												
LW	99.2	15.6	106.7	19.1	95.4	15.7	101.6	15.1	99.3	16.5	112.5	18.9
AP	101.9	18.2	109.2	16.8	94.1	18.6	107.1	15.9	101.1	14.1	115.5	16
BPI	7.49	4.83	7.96	5.95	7.2	4.68	7.67	4.93	8.04	6.36	7.91	5.63
Covariates												
Ageatpcg	60.6	13.3	121.8	22.1	61.2	12.9	60.2	13.5	123.1	22.5	120.8	21.7
RaceWhite	0.61	0.49	0.58	0.49	0	0	1	0	0	0	1	0
RaceBlack	0.39	0.49	0.42	0.49	1	0	0	0	1	0	0	0
Chgender	0.56	0.49	0.49	0.5	0.56	0.49	0.55	0.49	0.53	0.49	0.47	0.49
Birthorder	1.89	1.12	2.08	1.12	1.98	1.31	1.83	0.97	2.29	1.27	1.93	0.96
Birthweight	6.88	1.39	6.94	1.38	6.51	1.47	7.13	1.28	6.59	1.44	7.19	1.27
Ageatbreast	3.23	5.97	3.1	5.31	1.3	3.79	4.47	6.74	1.11	3.25	4.56	6
AgeBirthM	27.2	5.95	27.3	5.18	25.1	5.96	28.5	5.56	26.3	5.32	28.1	4.94
MaritalBirth	0.68	0.46	0.73	0.44	0.39	0.49	0.87	0.33	0.45	0.49	0.93	0.25
EducationM	13.2	2.02	13.1	2.14	12.5	1.77	13.6	2.04	12.4	1.87	13.5	2.19
ParentLive	0.66	0.47	0.66	0.47	0.38	0.48	0.85	0.36	0.42	0.49	0.84	0.37
ChildrenFU	2.22	1.03	2.42	1.02	2.26	1.21	2.19	0.9	2.52	1.21	2.35	0.83
AgeYoungest	3.41	1.58	7.27	3.14	3.49	1.52	3.354	1.62	7.19	3.41	7.32	2.93
OtherAdults	0.77	0.49	0.86	0.59	0.53	0.58	0.93	0.34	0.71	0.73	0.97	0.44
OwnHouse	0.56	0.49	0.66	0.47	0.31	0.46	0.72	0.45	0.47	0.49	0.8	0.40
EducationF	9.06	6.68	8.86	6.67	4.93	6.45	11.7	5.34	5.21	6.3	11.5	5.57
Avg(Total Income)	10.6	0.97	10.8	0.91	10.1	0.96	11	0.76	10.3	0.93	11.2	0.69
Mother's FE	-0.77	2.1	0.47	1.99	-1.36	2.02	-0.39	2.06	0.15	1.96	0.71	1.98
AvgWeeklyWage	561	76.9	567	86.3	543	64.7	573	81.8	554	86.9	576	84.5
Observations	516		936		220		341		396		540	

Figure 1. Dose response functions for **young** (column 1) and **old** (column 2) children and for maternal time (row 1) and school/care time (row 2)

Figure 1.1. Dose response functions for the reading skills score (LW)

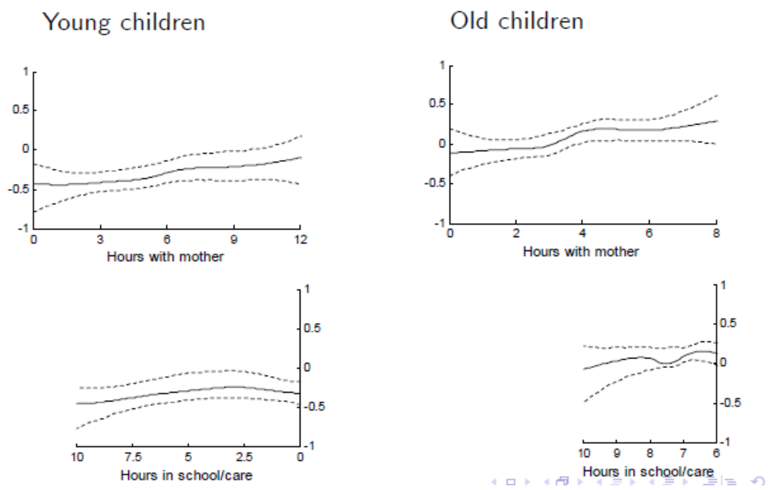

Figure 1.2. Dose response functions for the mathematical skills score (AP)

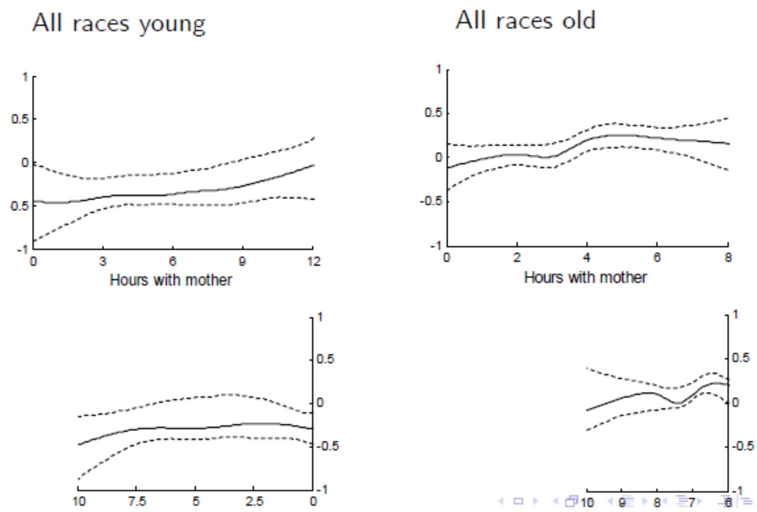

Figure 1.3. Dose response functions for the behaviour score (BPI)

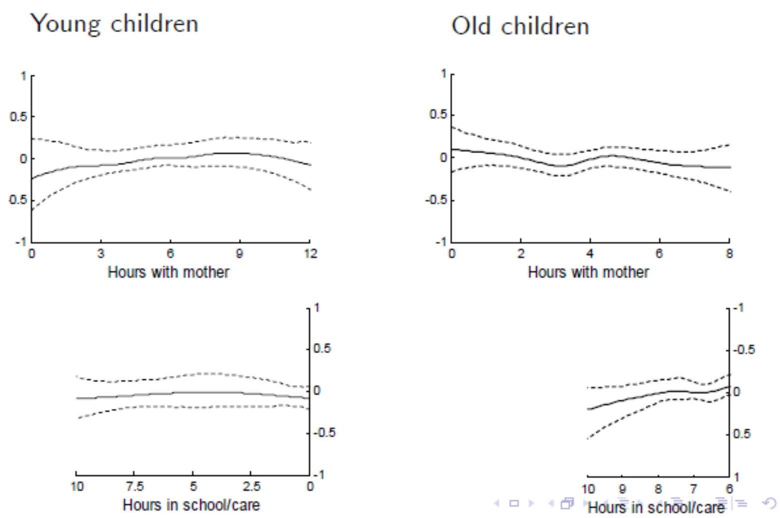

Table 3. Dose response differences for different levels of treatments: **young** (column 1) and **old** (column 2) children

LW

Young children					Old children				
M	0	3	6	9	**M**	0	2	4	6
3	0.02	-	-	-	2	0.05	-	-	-
6	0.14	0.12	-	-	4	0.27 *	0.22 *	-	-
9	0.22	0.20 *	0.08	-	6	0.28 *	0.24 *	0.01	-
12	0.34 *	0.32 *	0.19	0.12	8	0.39 *	0.35 *	0.13	0.11
S	0	2.5	5	7.5	**S**	6	7	8	9
7	0.07	-	-	-	7	-0.05	-	-	-
8	0.03	-0.04	-	-	8	-0.07	-0.02	-	-
9	-0.06	-0.13	-0.09	-	9	-0.10	-0.05	-0.03	-
10	-0.14	-0.21	-0.16	-0.08	10	-0.21	-0.16	-0.14	-0.11

AP

Young children					Old children				
M	0	3	6	9	**M**	0	2	4	6
3	0.05	-	-	-	2	0 .14	-	-	-
6	0.08	0.03	-	-	4	0.29 *	0.16 *	-	-
9	0.18	0.13	0.09	-	6	0.33 *	0.19 *	0.03	-
12	0.42	0.37 *	0.33 *	0.24	8	0.26 *	0.12	-0.03	-0.06
S	0	2.5	5	7.5	**S**	6	7	8	9
7	0.06	-	-	-	7	-0.12	-	-	-
8	0	-0.06	-	-	8	-0.11	0.01	-	-
9	-0.01	-0.07	-0.01	-	9	-0.15	-0.03	-0.04	-
10	-0.19	-0.25	-0.19	-0.18	10	-0.29	-0.17	-0.18	0.14

BPI

Young children					Old children				
M	0	3	6	9	**M**	0	2	4	6
3	0.14	-	-	-	2	-0.09	-	-	-
6	0.23	0.09	-	-	4	-0.12	-0.02	-	-
9	0.29	0.15	0.06	-	6	-0.16	-0.06	-0.04	-
12	0.15	0.01	-0.08	-0.14	8	-0.21	-0.11	-0.09	-0.05
S	0	2.5	5	7.5	**S**	6	7	8	9
7	0.05	-	-	-	7	0.07	-	-	-
8	0.06	0.01	-	-	8	0.08	0.01	-	-
9	0.03	-0.02	-0.03	-	9	0.16	0.09	0.08	-
10	-0.01	-0.06	-0.07	-0.04	10	0.27	0.2	0.19	0.11

Note: * indicates the difference is significant at least at 10% significance level

The first panel of each sub-table (**M**) presents the differences in the d.r.f. for maternal time. The second panel of each sub-table (**S**) presents the differences in the d.r.f. for school/care time.

Figure 2. Dose response functions for maternal time (row 1) and school/care time (row 2) and for **young** black children (column 1) and **young** white children (column 2)

Figure 2.1. Dose response functions for the reading skills score (LW)

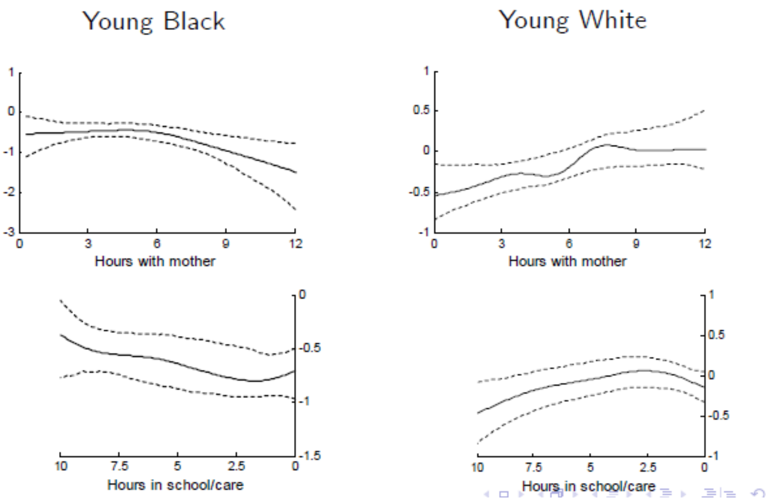

Figure 2.2. Dose response functions for the mathematical skills score (AP)

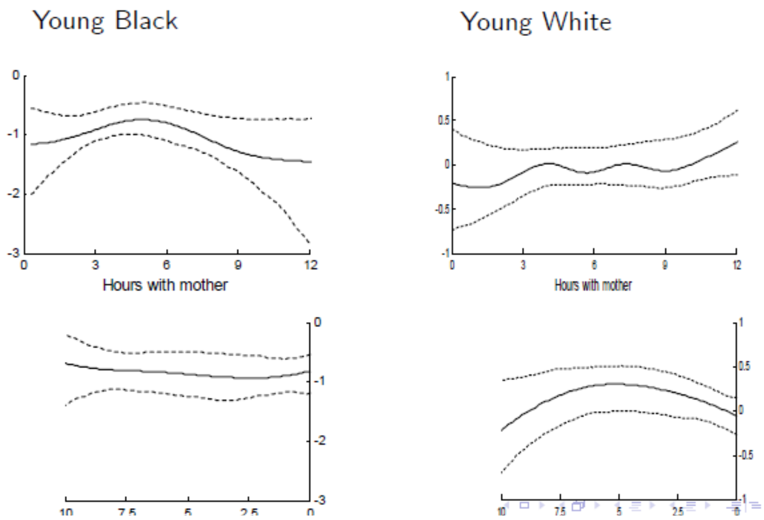

Figure 2.3. Dose response functions for the behaviour score (BPI)

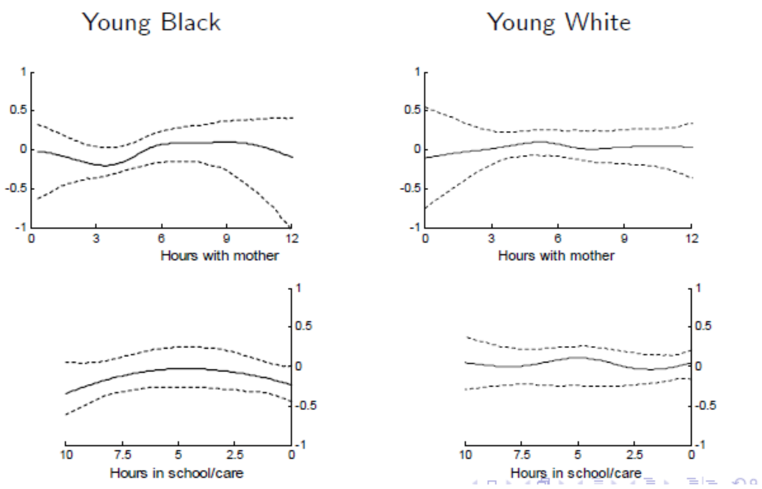

Table 4. Dose response differences for different levels of treatments: **young** black (column 1) and **young** white (column 2) children

LW									
Black					White				
M	0	3	6	9	**M**	0	3	6	9
3	0.07	-	-	-	3	0.23	-	-	-
6	0.00	-0.06	-	-	6	0.35 *	0.12	-	-
9	-0.47	-0.54 *	-0.48 *	-	9	0.56 *	0.33 *	0.21 *	-
12	-1.00 *	-1.07 *	-1.00 *	-0.53	12	0.57 *	0.34	0.22	0.01
S	0	2.5	5	7.5	**S**	0	2.5	5	7.5
2.5	-0.08	-	-	-	2.5	0.21 *	-	-	-
5	0.07	0.14 *	-	-	5	0.09	-0.11	-	-
7.5	0.15	0.23 *	0.08	-	7.5	-0.03	-0.25 *	-0.13	-
10	0.34	0.41 *	0.27	0.19	10	-0.32	-0.53 *	-0.42 *	-0.29 *

AP									
Black					White				
M	0	3	6	9	**M**	0	3	6	9
3	0.28	-	-	-	3	0.12	-	-	-
6	0.32	0.03	-	-	6	0.12	0.00	-	-
9	-0.16	-0.45 *	-0.48 *	-	9	0.1	0.01	0.01	-
12	-0.29	-0.58	-0.62	-0.13	12	0.46	0.34	0.34	0.32 *
S	0	2.5	5	7.5	**S**	0	2.5	5	7.5
2.5	-0.11	-	-	-	2.5	0.25 *	-	-	-
5	-0.05	0.06	-	-	5	0.36 *	0.10	-	-
7.5	0.01	0.12	0.06	-	7.5	0.23	-0.02	-0.12	-
10	0.13	0.25	0.18	0.12	10	-0.16	-0.42	-0.52 *	-0.39 *

BPI									
Black					White				
M	0	3	6	9	**M**	0	3	6	9
3	-0.17	-	-	-	3	0.12	-	-	-
6	0.11	0.27 *	-	-	6	0.18	0.06	-	-
9	0.12	0.29	0.02	-	9	0.14	0.02	-0.04	-
12	-0.10	0.07	-0.21	-0.23	12	0.14	0.02	-0.04	0.00
S	0	2.5	5	7.5	**S**	0	2.5	5	7.5
2.5	0.16	-	-	-	2.5	-0.07	-	-	-
5	0.21	0.05	-	-	5	0.06	0.13	-	-
7.5	0.11	-0.05	-0.09	-	7.5	-0.04	0.03	-0.11	-
10	-0.11	-0.27	-0.32	-0.22	10	0.00	0.07	-0.06	0.05

Note: * indicates the difference is significant at least at 10% significance level

The first panel of each sub-table (**M**) presents the differences in the d.r.f. for maternal time. The second panel of each sub-table (**S**) presents the differences in the d.r.f. for school/care time.

Figure 3. Dose response functions for maternal time (row 1) and school/care time (row 2) and for **old** black children (column 1) and **old** white children (column 2)

Figure 3.1. Dose response functions for the reading skills score (LW)

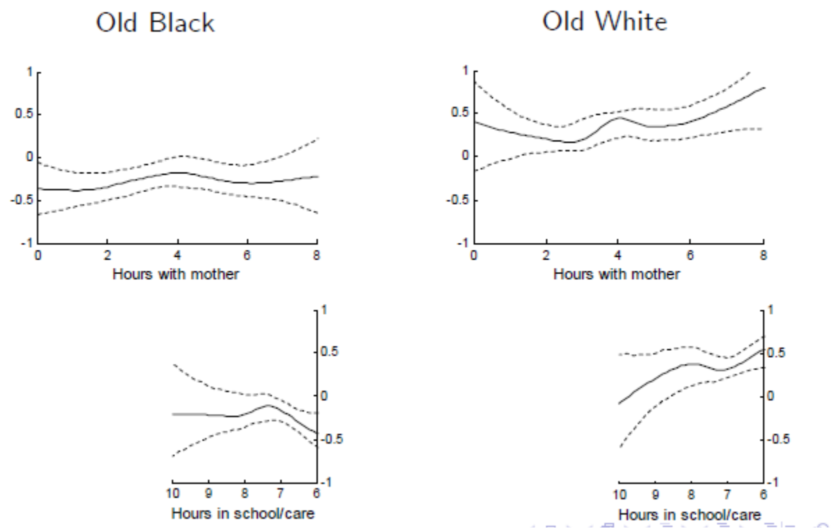

Figure 3.2. Dose response functions for the mathematical skills score (AP)

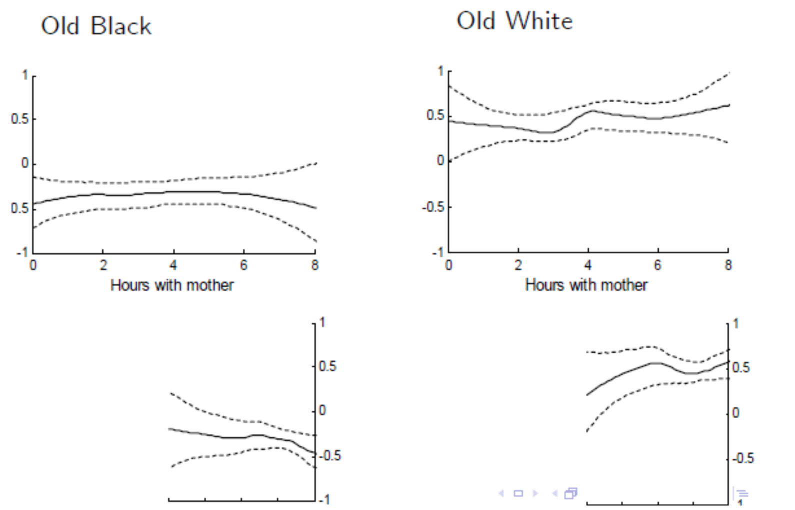

Figure 3.3. Dose response functions for the behaviour score (BPI)

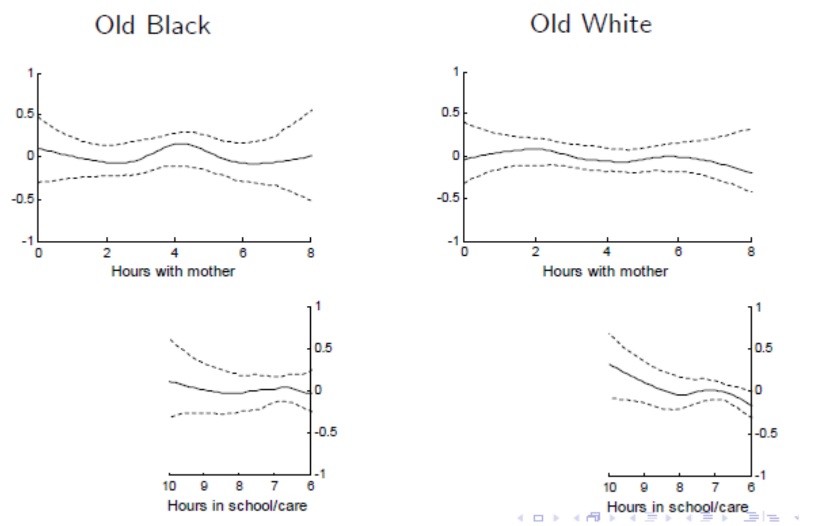

Table 5. Dose response differences for different levels of treatments: **old** black (column 1) and **old** white (column 2) children

LW									
	Black					White			
M	0	2	4	6	**M**	0	2	4	6
2	0.02	-	-	-	2	-0.2	-	-	-
4	0.18	0.16	-	-	4	0.04	0.24 *	-	-
6	0.07	0.10	-0.12	-	6	0	0.2	-0.04	-
8	0.15	0.13	-0.04	0.08	8	0.39	0.59 *	0.35	0.39 *
S	6	7	8	9	**S**	6	7	8	9
7	0.26 *	-	-	-	7	-0.21 *	-	-	-
8	0.22 *	-0.05	-	-	8	-0.15	0.07	-	-
9	0.21	-0.05	0.00	-	9	-0.34 *	-0.12	-0.19 *	-
10	0.22	-0.04	0.01	0.01	10	-0.63 *	-0.41	-0.48 *	-0.29 *

AP									
	Black					White			
M	0	2	4	6	**M**	0	2	4	6
2	0.11	-	-	-	2	-0.08	-	-	-
4	0.13	0.03	-	-	4	0.09	0.18 *	-	-
6	0.11	0.01	-0.02	-	6	0.03	0.11	-0.06	-
8	-0.04	-0.14	-0.17	-0.15	8	0.17	0.26	0.08	0.14
S	6	7	8	9	**S**	6	7	8	9
7	0.16	-	-	-	7	-0.12	-	-	-
8	0.17	0.01	-	-	8	-0.01	0.11	-	-
9	0.21	0.05	0.04	-	9	-0.14	-0.02	-0.13	-
10	0.27	0.11	0.10	0.06	10	-0.37	-0.26	-0.37	-0.23 *

BPI									
	Black					White			
M	0	2	4	6	**M**	0	2	4	6
2	-0.17	-	-	-	2	0.12	-	-	-
4	0.05	0.21 *	-	-	4	-0.02	-0.13	-	-
6	-0.17	-0.01	-0.22	-	6	0.03	-0.09	0.05	-
8	-0.09	0.07	-0.14	0.08	8	-0.15	-0.27	-0.13	-0.18
S	6	7	8	9	**S**	6	7	8	9
7	0.05	-	-	-	7	0.15	-	-	-
8	0	-0.05	-	-	8	0.1	-0.05	-	-
9	0.04	-0.01	0.04	-	9	0.26 *	0.1	0.16 *	-
10	0.15	0.09	0.14	0.1	10	0.49 *	0.33	0.38 *	0.23 *

Note: * indicates the difference is significant at least at 10% significance level

The first panel of each sub-table (**M**) presents the differences in the d.r.f. for maternal time. The second panel of each sub-table (S) presents the differences in the d.r.f. for school/care time.

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