Children's Skill Formation: The Role of Childhood Exposure to Pollution

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Abstract

Quite a few studies have recently examined the long term impact of pollution: normally, these studies focus on the relationships between childhood exposure to a specific type of pollution (e.g. air, water, lead, radiation) on the long-run outcomes such as schooling, health, or labor market. The literature, however, yet to address the underlying mechanism of these relationships. In this study I estimate a production function of skill formation for individuals at age 3-15 simultaneously accounting for their childhood exposure to pollution and the persistence of the negative effect of pollution on long term outcomes. The implications of this study are important from the policy perspective. Polices such as reduction of pollution level or income transfers to families, can remediate the negative impact of pollution and reverse the effects of childhood exposure to pollution during adulthood.

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1 Introduction

A notable number of studies recently examined the contemporaneous impact of pollution on public health[1]. The public burden of pollution forms one of the main bases for the environmental policies. However, less is known about the long term impact of pollution on formation of human capital. Few recent studies illustrate the long term impact of pollution on human capital and job market, yet there are still a lot to be learned in this area.

In this study, I use a structural model to estimate the impact of childhood exposure to pollution on educational performance of students. In this study, I estimate the impact of childhood exposure to pollution on educational outcomes. I use a structural model of skill formation that has at least two benefits in the context of pollution and human capital development. First, to account for endogeneity, I jointly solve a household optimization problem and derive the skill formation determinants. Furthermore, estimated parameters of the structural model allow me to conduct policy analysis and evaluate a counterfactual experiment.

Building on the existing studies, I develop a simple dynamic model of child's human capital formation process with a goal to estimate the technology of human capital. To estimate the model empirically, I combine the data from two data sets. The Panel Study of Dynamics (PSID) provides a rich panel on a nationally representative sample of households. The original PSID survey mainly focuses on the head of the household and the spouse but not on their children. Since 1997 the Child Development Supplement (CDS) is added to the original survey with the focus on the children in order to provide materials for childhood human capital formation studies. From the PSID and CDS I collect information on children and their family characteristics along with the households' investments on their children. To measure the pollution that children have been exposed to in their childhood I collect the pollution data from the US Environmental Protection Agency (EPA). The data set provides the pollution information that is recorded via

[1]For instance: Currie and Neidell (2005), Currie and Walker (2009), Currie, Neidell and Schmieder (2009)

the monitors throughout the country.

Consistent with the previous studies, my results demonstrate the negative effect of pollution on children's human capital. The elasticity of human capital with respect to pollution declines by child's age. One explanation is that the younger children are more susceptible to environment pollution than older children. These results also emphasize the importance of parents spending time with their children. Parents can boost their child's human capital by either directly helping them with regular school work or simply spending more time with them. However, the impact of formal schooling time on a child's human capital gets more important relative to parents time by a child's age.

2 Prior Literature

The difficulty of studying the long term impact of childhood exposure to pollution mainly can be due to limitation in data availability. The ideal data would contain the exact childhood exposure to pollution and a long term outcome such as educational attainments for the same individuals. In addition, it would have a rich information on other factors that are correlated with the environmental conditions that a child was exposed to and that had impact on the long term outcomes. These factors include but not limited to a child's health endowment, parents investment on their child, and parents' characteristics. To deal with these limitations, normally studies use natural/quasi experimental design or instrumental variable estimation.

Sanders (2011) studies the impact of prenatal exposure to total suspended particulate (TSP) on educational achievement in high school. He utilizes county-level variation in timing and magnitude of sudden change in TSP levels that happened in response to early industrial recession at early 1980s. He claims that the dramatic change in TSP levels is strongly correlated with the industrial and manufacturing production. He uses this relationship to construct an instrumental variable (IV) for TSP. Specifically, the IV for TSPs is defined as the relative share of county-level employment in manufacturing. The IV result is relatively larger than a simple OLS estimation.

He finds that one standard deviation reduction in TSPs leads to 6 percent increase in high school math scores for IV estimation. This number for OLS estimation is about 2 percent.

Almond, Edlund and Palme (2009) studies how well the children in Sweden who has been affected in utero by the Chernobyl disaster perform in school. The authors focus on children's achievement in the final year of compulsory school (age 16) and performance in high school (age 19). Although Sweden is very far from Chernobyl, but due to wind and weather conditions it received 5% percent of the fallout. Because of the weather condition there is a large variation in the amount of fallout among the affected regions in Sweden. This incident provides a natural experiment to study the impact of exposure to radiation on school performance of children. The study finds that the affected cohort by the fallout perform significantly worse in the final year of compulsory school and particularly in math. They also have a lower rate of high school graduation and lower GPA conditional on graduation. The authors also perform siblings estimation and they find a larger impact. From the perspective of the family response to the event, the results show that they play a reinforcement role.

Bharadwaj et al. (2014) examine the impact of exposure to air pollution during gestational trimesters on the educational performance in 4th grade in Santiago, Chile. One of the main contribution of this study is that it uses sibling comparison and air quality alerts to mitigate the sorting issue and the avoidance behavior as two main sources of biases. The idea is that by using sibling comparison they can control for factors that are correlated with pollution levels (through residential choice) and a child's educational achievement. For example, parents' income and their education level can be important determinants of residential choice and have a direct impact on a child's educational performance. If people respond to air quality alerts, by controlling for these alerts the authors take into account the subjects' avoidance behavior. The authors find a significant negative impact of pollution on math and language skills.

To the best of my knowledge Isen, Rossin-Slater and Walker (2014) is on of the first study that links childhood exposure to pollution directly to labor outcomes. The authors use the drastic change in TSP due to implementing the 1970 Clean Air Act Amendment (CAAA) to address the impact of childhood exposure to pollution on labor outcomes. The authors use the Longitudinal Employer Household Dynamics File (LEHD) data that allows them to estimate this relationship. They compare the labor outcomes of those who were born near before the CAAA implementation with those who were born near after the policy implementation in counties that experienced a sharp change in TSP levels. The study finds that 10 unit decline in TSPs in the year of birth is correlated with 1% decrease in annual earning of individuals in their late thirties. A back of the envelope calculation suggests that there is roughly $6.5 billion lifetime earning gain for the entire cohort that were affected by CAAA.

Lead exposure has a negative impact on the development of the central nervous system and brain. Higher lead level is associated with behavioral disorders such as aggressiveness, hyperactivity, and lack of emotional control. Reyes (2007) studies the impact of childhood exposure to lead on criminal activities in adulthood. She uses the variation of lead pollution levels among states over time due to removing lead from gasoline under the CAAA. She links the sharp drop of crime in 1990s to the decline of lead in the late 1970s and early 1980s. The author finds that the phase-out of lead from gasoline explains 56% of the decline in violent crime in 1990s. Following Donohue and Levitt (2001), Reyes controls for the abortion legalization as well. Her results support the Donohue and Levitt (2001) finding such that the abortion legalization is responsible for 29% of decline in crime.

Evens et al. (2015) study the impact of lead concentration in whole blood (B-Pb) on educational performance. The authors link three databases that gives them a rich data set on children and their family. They examine the impact of blood lead on 3rd grade Illinois Standard Achievement Tests (ISAT) scores in Chicago public schools. After controlling for family income, demographics, and very low birth weight or preterm-birth the authors find that even low blood lead levels[2] has a significant impact on educational performance. They find that $5\mu g/dL$ increase in B-Pb in early childhood is

[2] B-Pb of $< 10\mu g/dL$

associated with 32% increase in the risk of failing of the reading and math tests. Consistent with the previous studies, the results show that the impact of lead exposure is non-linear and it is steeper at lower levels.

In this study, I use a structural model to link the exposure to pollution of a child to an educational outcome. This method allows me to estimate a skill formation technology of child while controlling for pollution. Further, I control for the exposure to pollution of children over the development process and not just very early childhood exposure to pollution. The previous studies do not estimate the technology of the impact of pollution on the long term outcomes. Instead, they estimate a reduced form model. Estimating a structural model is important in order to do a policy analysis. If the theoretical model and the estimation results are accepted, having a structural model allows us to do a counterfactual analysis. For example, analyzing the impact of changing a factor, such as giving households education subsidy, on children's human capital. Further, all the studies focus on the prenatal exposure to pollution or at most the first two years of the childhood. Very early childhood is an important stage of a child's skill formation and is very vulnerable period to pollution. However, only focusing on the first two years of childhood does not capture the importance of the rest of the childhood.

3 Model

3.1 Model Setup

Conceptual model in this paper is based on studies by Cunha and Heckman (2007) and Boca, Flinn and Wiswall (2014). In the model each agent born with initial stock of skills/abilities, θ_0. The development process takes N periods. θ evolves over time according to the following technology[3]:

$$\theta_{t+1} = f_t(h, \theta_t, I_t, x_t), t \in 1, 2, ..., N \tag{1}$$

where t indexes time that is discrete with finite horizon. In the equation

[3] θ can be divided into cognitive and non-cognitive skills/abilities, but for now I suppress them as a skill/ability vector.

(1) h represents parental characteristics such as mother education, I_t is investment into a child's human capital. These investments consist of time that parents spend with their child, self-investment of the child (e.g. school time), and monetary expenditure, i.e. $I_t = (Time_{pt}, Time_{ct}, e_t)$.[4] p and c subscripts refer to parents and child, respectively. $Time_{pt}$ is the time that parents spend with their child and $Time_{ct}$ is the time that a child spends on investing in his human capital alone. In general, parental characteristics can include any factors relevant to development of a child's human capital. However, for now I only control for mother's education level [5].

At the beginning of every period a household has information on their child's human capital, income, and pollution level. A household makes the optimal decision as a unit and there is no bargaining among household members. A household optimally decides how to allocate their time among leisure and investment on a child's human capital, either a child's investment alone or with parents, and also how to spend their income on consumption and investment on children. A household receives utility from consumption, leisure, and children skills stock. The households utility in the last period of child development is $\beta\varphi \ln \theta_{N+1}$. This means that after a child reaches the age of N, a household receives a utility from the child's human capital at the end of the period N, and then the child leaves the household. The value function of household in period t is

$$V_t(\theta_t, b_t, x_t) = \max_{Time_{pt}, Time_{ct}, l_{pt}, l_{ct}, c_t, e_t} u(c_t, l_{pt}, l_{ct}, \theta_t) + \beta E_{b_{t+1}, x_{t+1}} V_{t+1}(\theta_{t+1}, b_{t+1}, x_{t+1}) \tag{2}$$

subject to

$$T = Time_{pt} + l_{pt}$$

$$T = Time_{pt} + Time_{ct} + l_{ct}$$

$$c_t + e_t = b_t$$

where b_t is a household's income and it is assumed to be exogenous and

[4] Boca, Flinn and Wiswall (2014) divide the time spending with children into two groups of active and passive time.

[5] Other characteristics will be added in the future version of the study.

stochastic, l_{pt} is parents leisure, l_{ct} childs leisure, β is discount factor, T is the total time available, and E is the conditional expectations operator with respect to the period t information set.

3.2 Pollution Impacts

Potentially, pollution can have a direct or indirect impact on a child's human capital. It affects human capital directly through child's health. Pollution can have mild health effects such as headache and tiredness, or severe health impacts such as asthma attack and long lasting brain damage from exposure to pollution in early childhood[6]. Poor health can affect a child's productivity in short term such as his performance at the school due to lack of attention or tiredness. Severe health shock such as nervous system damage can have a persistent and long term impact on a child's performance (Reyes (2007)).

Pollution also affects human capital indirectly through a household's behavior. Equation (3) demonstrates both effects of pollution. Using the equation (1) the partial derivative of θ_{t+1} with respect to x_t is

$$\frac{\partial \theta_{t+1}}{\partial x_t} = \underbrace{\frac{\partial f_t}{\partial e_t^*}\frac{\partial e_t^*}{\partial x_t} + \frac{\partial f_t}{\partial Time_{pt}^*}\frac{\partial Time_{pt}^*}{\partial x_t} + \frac{\partial f_t}{\partial Time_{ct}^*}\frac{\partial Time_{ct}^*}{\partial x_t}}_{IndirectImpact} + \underbrace{\frac{\partial f_t}{\partial x_t}}_{DirectImpact} \tag{3}$$

The asterisks indicate the optimal values of the decision variables. The three terms on the right hand side of equation (3)represent the indirect effect of pollution. This indirect effect on a child's human capital enters through the household's decision. In period t a household observes the pollution levels and decide to invest in the human capital of their child accordingly, $\partial I_t / \partial \theta_t$. Potentially, the household's response can be compensatory, $\partial I_t / \partial x_t < 0$, or reinforcing, $\partial I_t / \partial x_t > 0$. The last term on the right hand side is the direct impact of pollution described above.

[6] There are many research that show the negative health impact of pollution. For example: Currie and Neidell (2005), Currie and Walker (2009), Currie, Neidell and Schmieder (2009), Reyes (2007).

4 Model Solution

To solve the model I assume a simple Cobb-Douglas[7] functional form for both household's utility function and a child's skill technology. The household's preferences are represented by

$$u(c_t, l_{pt}, l_{ct}, _t) = \alpha_1 lnc_t + \alpha_2 lnl_{pt} + \alpha_3 lnl_{ct} + \alpha_4 ln\theta_t, \tag{4}$$

where $\sum_j \alpha_j = 1$ and $\alpha_j > 0$ for $j = 1, .., 4$. The technology function is as following

$$\theta_{t+1} = h_t^{\delta_{1,t}} \theta_t^{\delta_{2,t}} e_t^{\delta_{3,t}} Time_{pt}^{\delta_{4,t}} Time_{ct}^{\delta_{5,t}} x_t^{\delta_{6,t}}, \tag{5}$$

Therefore, a child's human capital at the end of period t, θ_{t+1}, depends on his parent's characteristics, h, his stock of human capital at the beginning of the period, θ_t, money and time investments, and exogenous factor, x_t. Self productivity of the technology function is described as ${}^{\partial\theta_{t+1}}/_{\partial\theta_t} > 0$, meaning that starting a period with high skill level leads to accumulating more of skill. In the equation (5) all the $\delta_{i,t}$ for $i = 1, .., 5$ that represent the elasticity of the determinants of human capital, are positive. Only pollution has a negative impact on a child's human capital and it means that $\delta_{6,t}$ is negative.

Due to the Cobb-Douglas form of utility and technology functions, all the optimal decision variables would be independent of pollution levels. Potential candidate among the decision variables to be dependent on pollution levels is the expenditure variable, e_t. To allow for that dependence, I choose a simple linear combination of the expenditure and pollution variables $\tilde{e}_t = e_t + p_1 e_t x_t + p_2$ and use it directly in the technology function. For example, if a child has asthma problem and pollution goes up, medical expenses of household may go up too. As another example, parents may keep their child at home in a bad air pollution day and spend on tutoring.

For the given functional forms of the utility function and the human capital technology the closed form solution[8] for the optimal decision variables

[7] Instead of the Cobb-Douglas form of utility function I could use more general form of the Constant Elasticity of Substitution (CES) model.

[8] I allow the corner solution in my model, however because of the Cobb-Douglas form

are

$$e_t^* = \frac{\beta\delta_{3,t}(1+p_1x_t)A_t - \alpha_1 p_2}{(1+p_1x_t)(\alpha_1+\beta\delta_{3,t}A_t)}, \tag{6}$$

$$Time_{pt}^* = \frac{\beta\delta_{4,t}A_tT}{\alpha_2+\alpha_3+\beta(\delta_{4,t}+\delta_{5,t})A_t}, \tag{7}$$

$$Time_{ct}^* = \frac{\beta\delta_{5,t}A_t(T-Time_{pt}^*)}{\alpha_3+\beta\delta_{5,t}A_t}, \tag{8}$$

$$l_{pt} = T - Time_{pt}^*, \tag{9}$$

$$l_{ct} = T - Time_{pt}^* - Time_{ct}^*, \tag{10}$$

For N periods of child development process A_t is calculated as

$$A_N = \varphi, \tag{11}$$

$$A_{N-1} = \alpha_4 + \beta\delta_{2,N}\varphi,$$

$$\vdots$$

$$A_t = \alpha_4 + \beta\delta_{2,t+1}A_{t+1},$$

$$\vdots$$

$$A_1 = \alpha_4 + \beta\delta_{2,2}A_2,$$

A closed from solution allows to derive an explicit expression of the direct and indirect impact of pollution on child's skill can be derived. Using equations (5), (3), and (4) the direct impact is

$$DirectImpact = \frac{\partial f_t}{\partial x_t} = \frac{\delta_{6,t}\theta_{t+1}}{x_t}, \tag{12}$$

$$\text{Indirect Impact} = \frac{\partial f_t}{\partial e_t^*}\frac{\partial e_t^*}{\partial x_t} = \frac{\alpha_1 p_1 p_2 \delta_{3,t}\theta_{t+1}}{(1+p_1x_t)[\beta\delta_{3,t}(1+p_1x_t)A_t - \alpha_1 p_2]}, \tag{13}$$

of the preferences and the skill formation there is no corner solution. If any of the decision variable is zero, then one of the elements in the preference function is zero and the value of the utility function will go to negative infinity.

Since $\delta_{6,t}$ is negative, the direct impact is negative. Theory does not give an unambiguous predictions with respect to the scale of $\delta_{6,t}$, it is therefore not clear how the impact varies by the pollution levels. As expected, the indirect impact is positively related to $\delta_{3,t}$. In the theoretical model there is no restriction on the sign and the level of the parameters p_1 and p_2, thus, the effect of p_1, p_2, and α_1 on indirect impact of pollution is not clear.

5 Data

Primary source of data for this study comes from the Panel Study of Income Dynamics (PSID) and three waves of Child Development Supplement (CDS-I, CDS-II, and CDS-III). I also use pollution data from the US Environmental Protection Agency (EPA).

5.1 PSID and CDS

The PSID is a nationally representative longitudinal study of the US individuals and families in which they reside. It provides wide range of information on families and individuals. Since 1968 the PSID has collected data on family composition changes, housing and food expenditures, marriage and fertility histories, employment, income, health, consumption, wealth, and time spent on housework. I use demographics information about the parents of children from the main PSID survey. The original PSID survey mainly focuses on households and particularly the heads of the household, and then on spouses. Although the PSID has always collected some information about children in these families, there was less known about them. Starting at 1997 the PSID added the CDS that focuses on children and collects detailed information on them.

The CDS collects general school achievement information and also administers the subset of standard tests to assess academic skills of children. These tests include mathematics and language skills among other content areas. For this study I use the Letter-Word (LW) test scores as a measure of educational achievement. The LW test is a subset of Woodcock-Johnson

Revised (WJ-R) test of achievement that measures the symbolic learning and reading identification abilities of children at ages between 3 to 17. I use the raw scores for the LW test that is well-suited for examining changes in a child's performance on a WJ-R sub-test over time[9].

The CDS also collects time diary data on children for two days during a week: one weekday and one weekend day. Subjects fill out (with their caregiver if they are too young) a detailed time diary during these days. They provide information on what they have done (type of activity), where they have done (location of activity), starting and ending time of activity (duration of activity), and who was with them during the activity over 24 hours a day of survey. I use the time diary information to extract the time that children spend on their human capital, either alone (e.g. time at school or working alone on home works) or with their parents (studying with parents). Table 1 lists the variables that I use, years of data, and their sources. I only focus on years 1997, 2002, and 2007 when CDS has been administered. Since I am interested on the development of a child human capital I only keep children who have LW test score at 1997 as the beginning period. I also drop children for whom I do not have their family income in 1997. Given that income in my model is the available income to spend on all the family's expenses, I drop all observations that have less than zero dollar or above \$150000 annual income and replace less than \$150 weekly income with \$150 [10].

Table 2 provides summary statistics of the data from PSID and CDS. All the time variables are calculated in hours per week units and the family income is weekly income in 2000 dollars. Table 3 presents demographics variables for the CDS sample started at 1997.

[9]The PSID also reports the standard scores of the LW test that are standardized using a child's raw score, his age, and other children's scores in his age category. The standard scores are useful for cross-sectional comparison between different age groups. However, it is not useful to study changes in a child's performance over time.

[10]Some of the families have income of zero or negative which corresponds to business or farm losses. The percentage of households with zero or negative income is only 5% of all the households with non-missing income.

5.2 Pollution

The ideal air pollution data would be the exact measure of pollution that a child has inhaled. Unfortunately, such detailed and exact measure of exposure to pollution is not available unless it is recorded in a lab experiment. In case of the United States, researchers normally use the measure of pollution that is recorded by the EPA via numerous monitors throughout the country. For this study I use ozone as the pollution measure. Since the main data from the PSID is collected on yearly basis, the pollution data should match that annual pattern. Instead of reporting an annual measure collected form the monitors, the EPA generates so-called "Design Value". The design value is a statistic that the EPA generates to describe the air quality status at a particular location relative to the National Ambient Air Quality Standards (NAAQS). Based on the design value, the EPA determines if a particular monitor or, in a more aggregate level, a county is in attainment status or not. If the design value is above a threshold the monitor or the county is considered to be in non-attainment and if it is below that it is considered to be in attainment status. If a county is in non-attainment status it should lower the pollution levels below the designed threshold. Under the Clean Air Act Amendment (CAAA) every year the EPA assigns a county attainment/non-attainment status. In order to make the interpretation of the estimation results easier I divide the design value by its standard deviation. Figure (4) shows the distribution of the pollution data and it has a high variation. Figure (5) shows a simple linear correlation between the pollution variable and the LW test scores and the correlation is negative. However, this negative correlation is not consistent for different ranges of the pollution variable. If we only look at the points above the median level of the pollution variable, the negative correlation is more prominent. Figure (6) shows this relation. The simple correlation of the pollution variable and the LW test score for values above the median is around -0.201 and for values below the median is around 0.006. This simple correlation suggests that the impact of pollution on test score potentially can be non-linear.

6 Estimation Method

In this section I explain the assumptions regarding the model specification and the identification of the parameters of the model.

6.1 Parameters

In equation (5) I allow the production parameters, $\delta_{i,t}$, to vary by a child's age. In order to economize on parameters, instead of estimating $6N$ production parameters I assume a log linear form for $\delta_{i,t}$'s as following

$$\delta_{i,t} = exp(\lambda_{i,1} + \lambda_{i,2}t), i = 1, ..., 6; t = 1, ..., N, \tag{14}$$

Using this linear form, the total number of technology parameters to be estimated reduces to only 12.

Household utility parameters are assumed to be constant over time. For simplicity I assume that all households exhibit homogeneous preferences. The standard assumptions of $\sum_j \alpha_j = 1$ and $\alpha_j > 0$ for $j = 1, .., 4$ normalize the utility function and ensure that preferences are increasing in all the elements. Because of the normalization I only need to estimate three of α_j's using the following mapping

$$\begin{aligned} \alpha_1 &= D^{-1} exp(\upsilon_1), \\ \alpha_2 &= D^{-1} exp(\upsilon_2) \\ \alpha_3 &= D^{-1} exp(\upsilon_3), \\ \alpha_4 &= D^{-1}, \end{aligned} \tag{15}$$

where $D^{-1} = 1 + \sum_{k=1}^{3} exp(\upsilon_k)$. Instead of estimating α_j's directly, I will estimate three υ_k's.

I assume that households income follows a Markov process as following

$$lnb_{t+1} = B_0 + B_1 lnb_t + \varepsilon_{t+1}^b, \quad \varepsilon_t^b \sim Normal(0, \sigma_1), \tag{16}$$

In the first period, households start with income level b_1. Later, in the estimation of the model I choose b_1 from the actual data. Household's income for the beginning period is the household's income at 1997 from the data.

6.2 Identification

I start with the estimation of three of the preference parameters, α's. Larger values of α_2 indicate higher valuation of parental leisure time by household. Therefore, parents will spend less time with their child, i.e. smaller $Time_{pt}$. By the same logic, the larger α_3 leads to less time on education in overall time, i.e. $Time_{pt} + Time_{ct}$. However, there is a trade off between spending time on a child's human capital and leisure. On the one hand, spending more time on a child's human capital leads to higher utility from boosting child development, $\alpha_4 ln\theta_t$. On the other hand, investing on a child's human capital leaves a household with less time for leisure and reduces household's utility. The variation in time spent on a child's human capital by parents and alone that is observable in the data allows to estimate the relative values of α_2, α_3, and α_4.

In equation (5) δ's are the elasticities of human capital at the end of each period, θ_{t+1}, with respect to the factors that affect a child's human capital. The panel data on test scores and the determinant factors of the skill formation provide variation both across children and over their development process. This variations enables me to estimate δ's. Ceteris paribus, variation in pollution levels and its correlation with child's test scores gives the estimation of δ_6. In the same way I can estimate the rest of δ's.

In addition to α's and δ_i's there are four other parameters that must be estimated. These parameters are β, φ, p_1, and p_2. In total, there are 19 parameters[11] to be estimated. I use average and standard deviation of three variables: time that parents spend with their child, total time that a child invest on his human capital, and the LW test scores. I calculate these moments for four age categories of 3-6, 7-10, 11-15, and 16-18 ages. So there are 24 moments in total which is sufficient to estimate the 19 parameters.

[11] Twelve λ's, three α's, β, φ, p_1, and p_2.

7 Estimation Results

In this subsection I present the estimation results of the theoretical model. Time periods are years and I assume that child development lasts until age 15, so that $N = 15$. Even though the development of a child continues after age 15, it is no longer included in the household's preferences. In the last period of the development process, a household only cares about the child's human capital at the end of that period. First, I present the estimated parameters and then within sample test of the model.

7.1 Household Preference Parameters

Although it is very strong assumption, but for simplicity in the current version of the paper I assume that households are homogeneous regarding their preferences. Preference parameters are presented in the table 4. Households put similar weights on leisure of parents and children and it is about 0.20. Households value their child's human capital much higher: at 0.35 it is weighted 75% more than each of parents or child leisure time. The estimated scaling factor for child's human capital at the last period is .50.

7.2 Child Human Capital Technology Parameters

In order to estimate elasticities of human capital with respect to other factors, I first need to estimate technology parameters, λ's. However, interpreting λ's separately is not very intuitive. Instead, presenting the value of δ's are more informative. Figures 7-9 show the value of δ's by child age over the child development horizon. Figure 7 demonstrates an increasing pattern of the elasticity of child's human capital with respect to pollution by child's age. This means that younger children are more susceptible to pollution and they become stronger as they grow older. Figure 8 shows the elasticity with respect to time investment on child human capital, both parents' time and a child's alone time on education. Based on figure 2 not only parents spend less time with their child as the child grows older, the decreasing value of δ_4 also shows that their time gets less productive. However, a child's time in school or spending time alone on education becomes more effective as they grow older. Figure 9 shows the self-productivity of child's human capital. The increasing pattern means the larger the human capital with which a child starts a period, the larger the human capital he ends up with at the end of the period.

7.3 Within Sample Fit

In order to test how well the model fits the data I do a within sample fit test and present results in tables 5 and 6. For three age categories I compare the average value of the time that parents spend with their child, time that a child spend on education without his parents, the LW test scores from the data, and the simulated data. As can be seen, some of the means do not fit well. In estimating the parameters I use the moments for three age categories to fit the data. One of the main measure that I use to fit the model is the LW test scores. As evident from figure 10 the LW test scores in the true data is a convex function of children age, however in the simulated data it is a smooth concave function. This difference in curves' shapes makes it difficult to fit the data well for all age groups.

8 Counterfactual Analysis

In this section using the result of the point estimates, I examine the impact of two potential policies. The first policy is an environmental policy that exogenously increases the pollution level. The second policy is the transfer from the government to families. The experiments are to examine the impact of these policies on households' decisions and their child's human capital development.

8.1 Change in Pollution Level

Having a good understanding of the costs and benefits of an environmental policy is critical for its consideration and implementation. The impact of lowering pollution on children's human capital is one of the main benefits that we know less about. In this section I examine the impact of policy that reduces pollution given the point estimates derived from the previous analysis.

I select two random samples from the data. Keeping everything as it is in the data, I only add an exogenous variation to pollution levels. In one of the samples I increase the average pollution level that a household is exposed to by one standard deviation of the design value mean (treatment sample). In the control sample, the average level of pollution stays the same over the entire period of child development. Comparing the distribution of decision variables and the human capital of children in these two samples shows the impact of increase in pollution levels.

Figure 11 shows the distribution of children's LW test scores for two different pollution levels. The green curve is without an exogenous shock and the the red one is with the exogenous increase in the design value level. As expected when the pollution levels increase the distribution of children's test scores shifts down and it reduces the average test scores about 2%. The graph shows heterogeneity in response to change in pollution level among different ages. To show this heterogeneity, I draw the distribution of the difference between two curves in the graph for three age groups: 3-6, 7-10, and 11-15 years of age. Figures (12), (13), and (14) depict these distributions. Large portion of the distribution for the middle age group is larger than two other groups, meaning they are more affected by the pollution shock.

8.2 Income Transfer

Income transfer is one of the most common methods in child development policies to influence the children's skills and it is often used to target disadvantaged families. It is important to examine how the transfer to families can influence their decision and, in particular, their child's human capital. To test the effect of this policy, similar to the previous policy experiment I select two random samples. However, in this case I transfer an exogenous amount to households in one of the samples. Then compare the results of model solution for these two samples.

Figure 15 demonstrates the result of income transfer on child's human capital. In the treatment sample, households receive weekly transfers of \$200 from policy, and in control sample there is no transfer. The green curve represents the control sample and the blue one is for the treatment sample with transfer of \$200. As can be seen, the blue curve shifts up compared to the green one. The transfer of \$200 increases the average LW test scores by 0.2% that is one tenth of the impact of increase of the design value by one standard deviation.

9 Conclusion

In this study I estimate skill formation of children while including PM2.5 pollution as one of the determinants of human capital. I choose PM2.5 as a control for pollution exposure of children because it is one of the most hazardous pollutants to human health. I use a panel data from the PSID to collect the LW test score and time diary of children, and demographics of children and their family. I merge this panel with the PM2.5 measures from the EPA. Using the census block of households and the exact geographical location of monitors I assign PM2.5 measure using the nearest monitor to every household.

My results show that households value equally both parents' and child's leisure time[12]. Further, the weight that households assign to the child's human capital is significant[13]. My results also show the negative effect of pollution on the LW test scores. This effect if not uniform over the age of children. Consistent with the literature, the younger children are more susceptible to pollution than their older fellows. Consistent with the previous studies, parents' time spending with children and child's time on education are important determinants of the LW test score. However, these factors' productivity varies by child's age. Over the age of the child, parents' time productivity declines and the child's alone time on education become more productive.

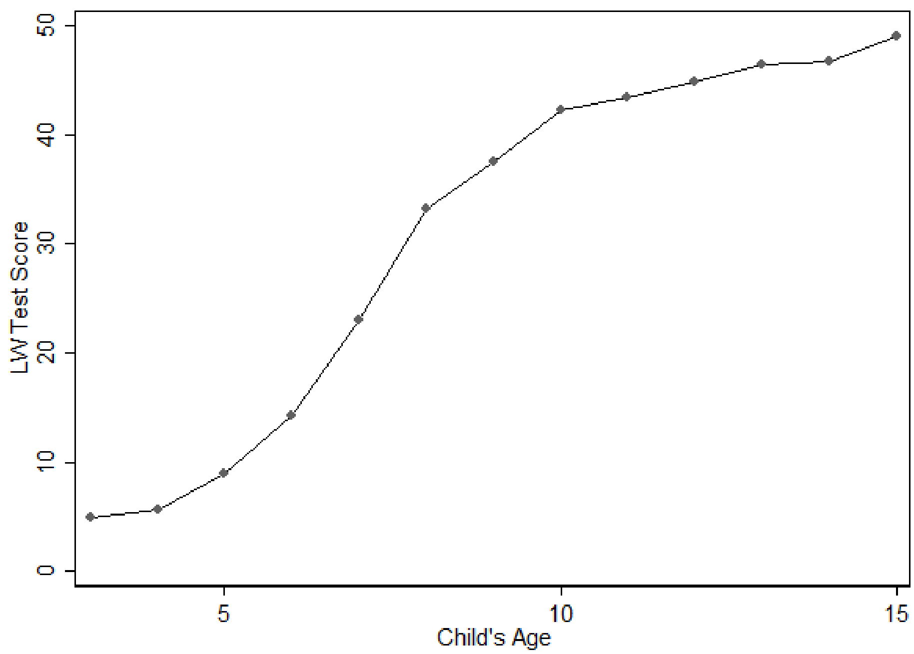
[12] $\alpha_2 = \alpha_3 \simeq .2$

[13] $\alpha_4 = .35$

After estimating the model I run two experiments. In the first experiment, I increase the pollution level by one standard deviation over the course of a child's age. On average, reducing one standard deviation PM2.5 increases the LW test score by 6% of standard deviation. In the second experiment, I give a transfer of $200 to every household. On average this transfer increases the LW test score by .4% of standard deviation.

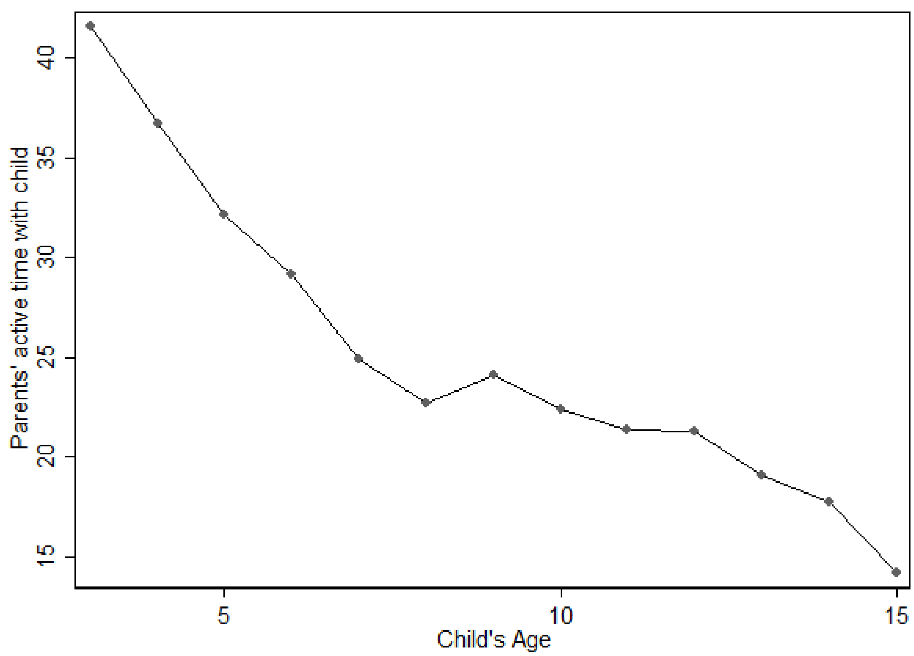
A Figures

Figure 1: Average LW Test Scores by Age



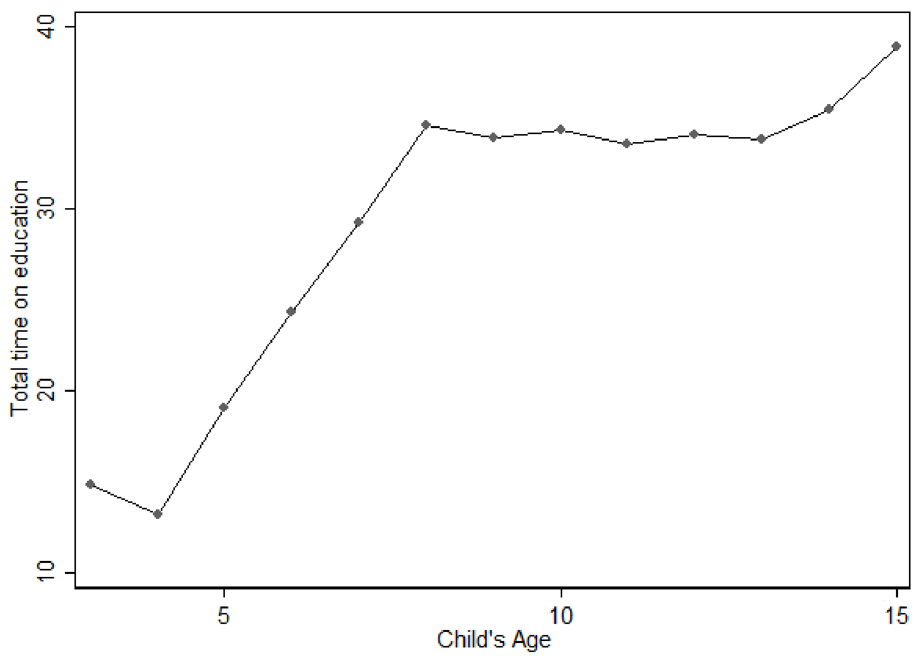
Source: PSID-CDS

Figure 2: Average Parents' Active Time with Child



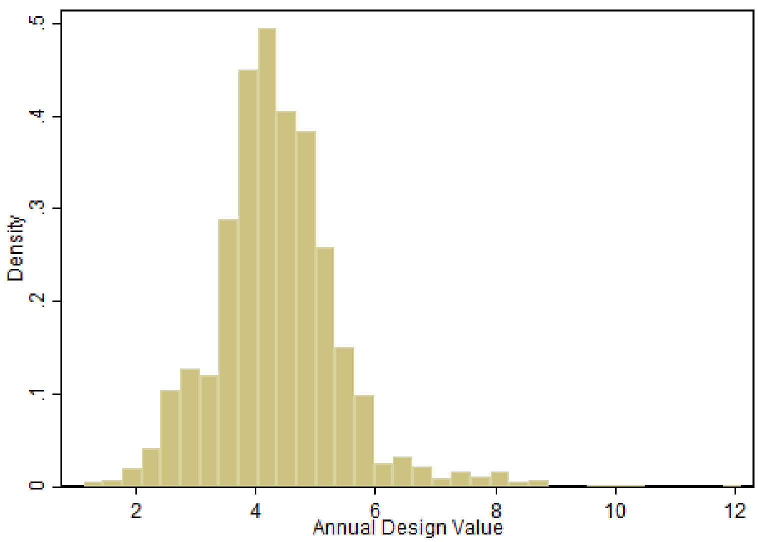
Source: PSID-CDS

Figure 3: Average Child's Time on Education Alone



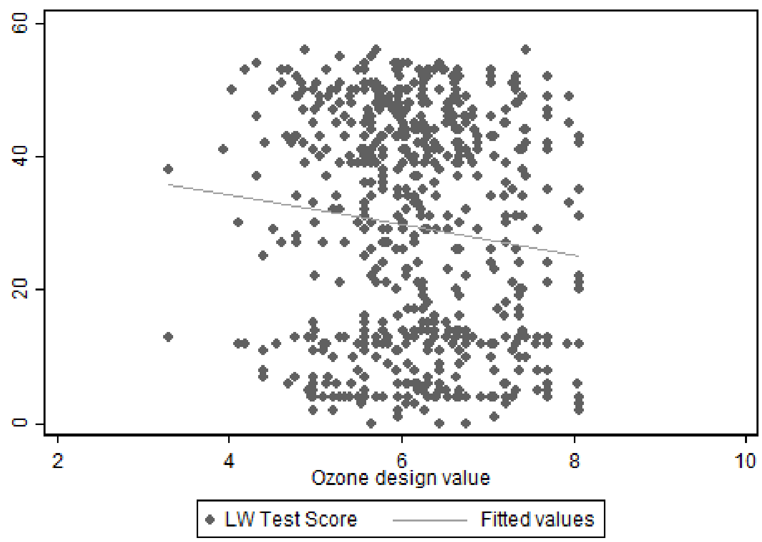
Source: PSID-CDS

Figure 4: Pollution Distribution



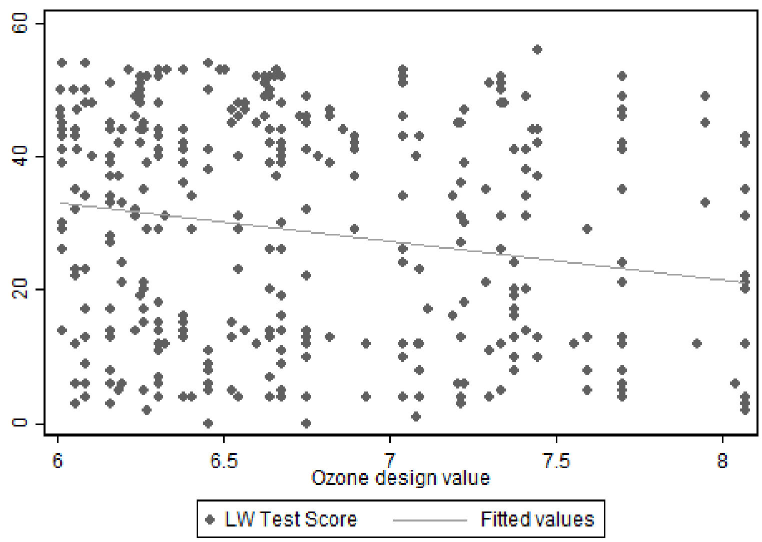
Source: EPA

Figure 5: Pollution Distribution



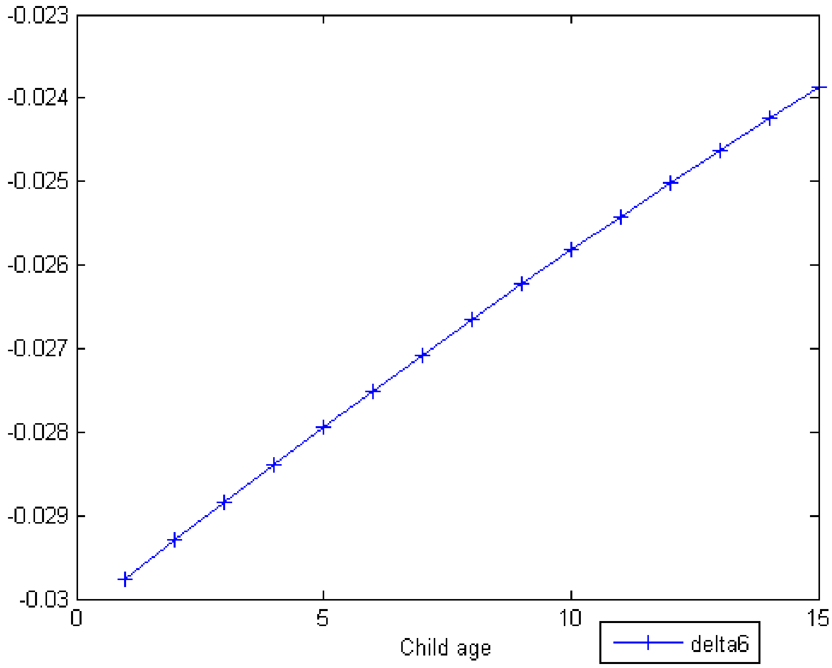
Source: EPA

Figure 6: Pollution Distribution



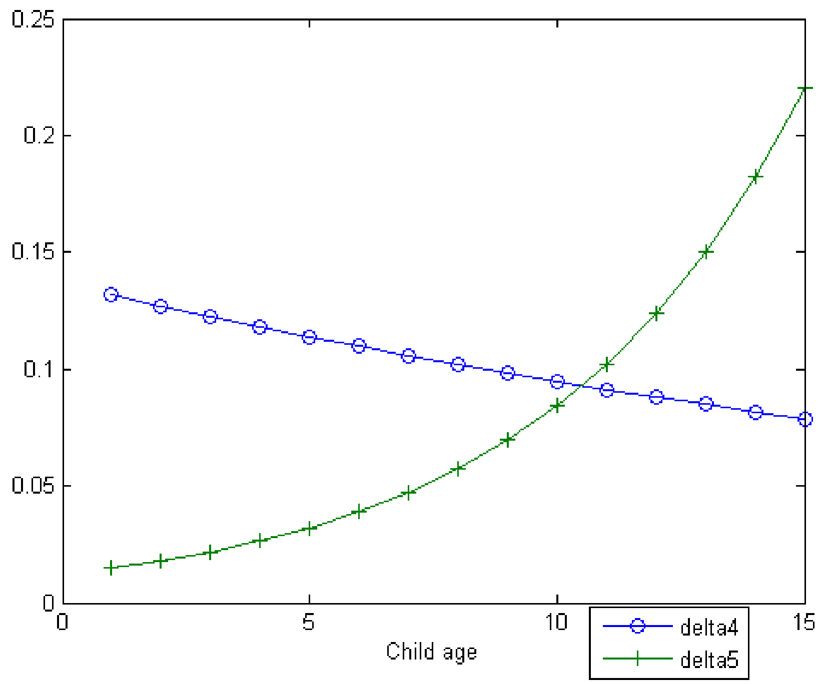
Source: EPA

Figure 7: Estimate of δ_6 by Age



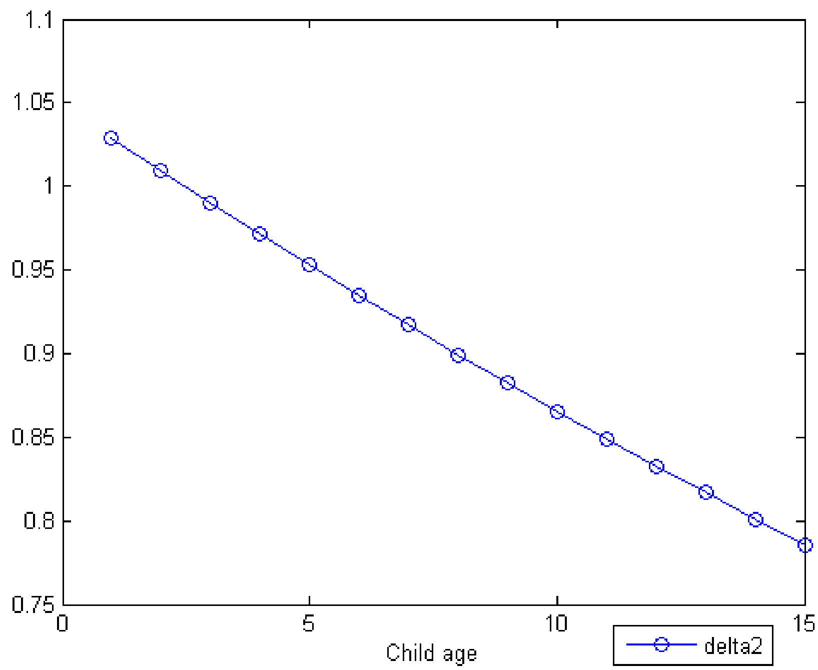
Note: δ_6 is the elasticity of test score, θ_{t+1}, with respect to pollution.

Figure 8: Productivity of Time by Age



Note: δ_4 is the elasticity of test score, θ_{t+1}, with respect to parents' time and δ_5 is with respect to child's total time on education.

Figure 9: Self-Productivity of θ



Note: δ_2 is the elasticity of θ_{t+1} with respect to θ_t

Figure 10: LW Test Scores by CHild's age in the True and Simulated Data

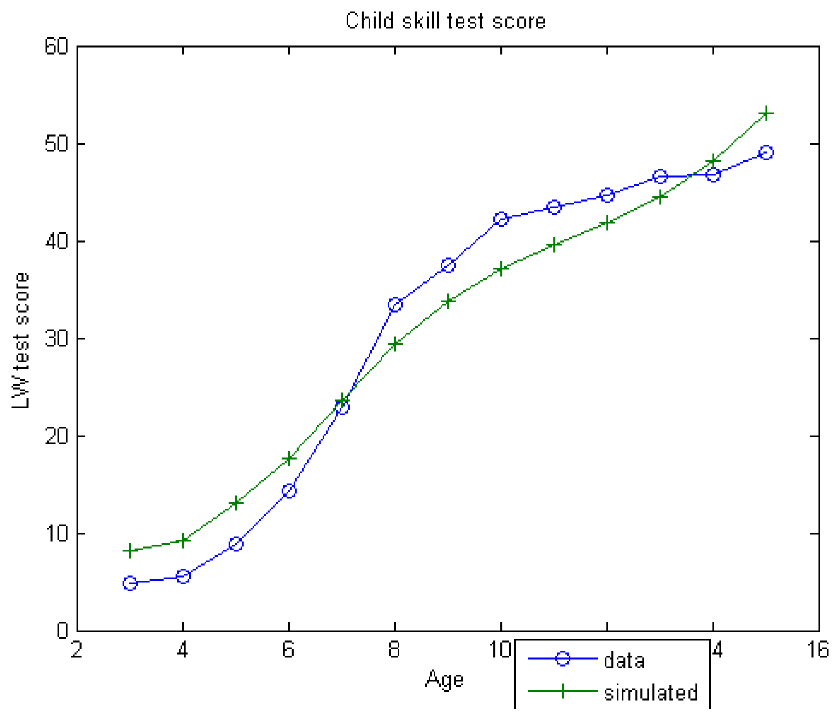
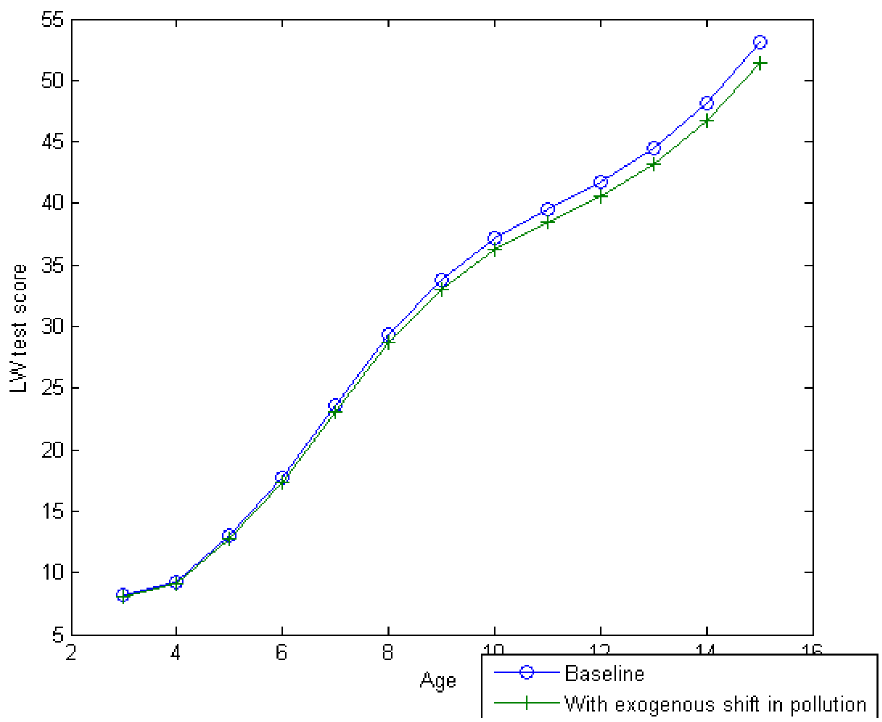


Figure 11: Average Child's Test Scores



Note: In the baseline I draw the pollution value from the data. For the treatment group, I add one standard deviation to the pollution stream in all the ages of a child.

Figure 12: LW test score change due to pollution shock. Age 3-6

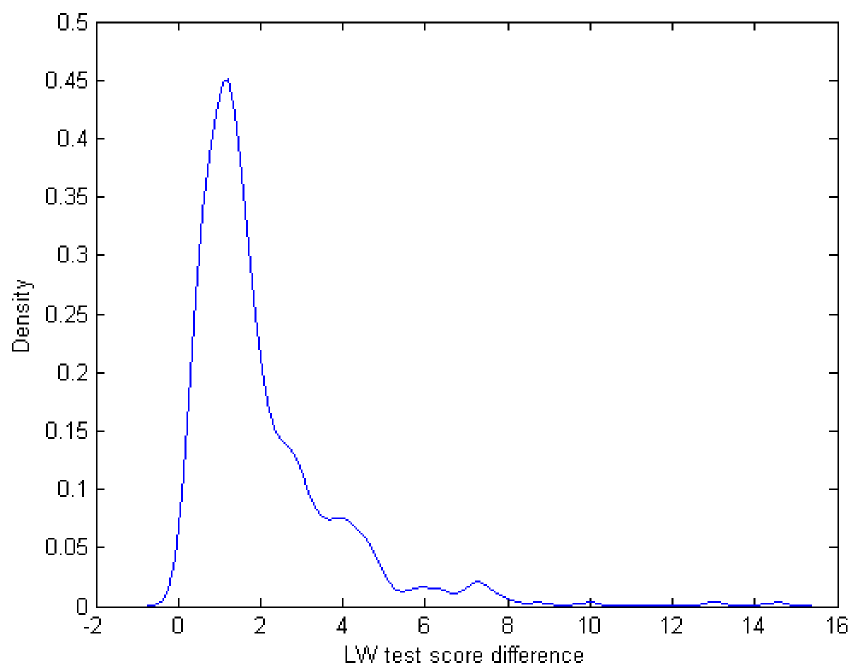


Figure 13: LW test score change due to pollution shock. Age 7-10

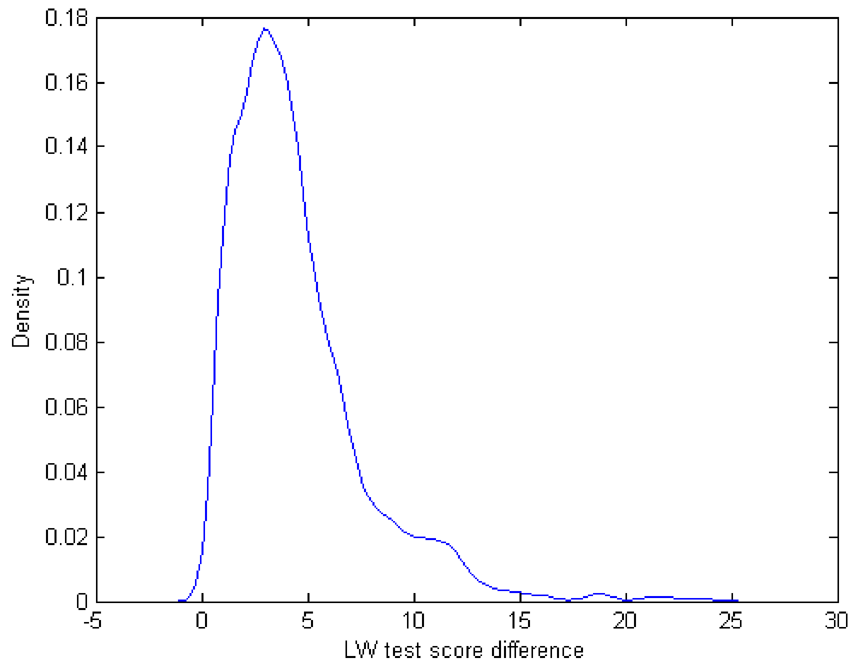


Figure 14: LW test score change due to pollution shock. Age 11-15

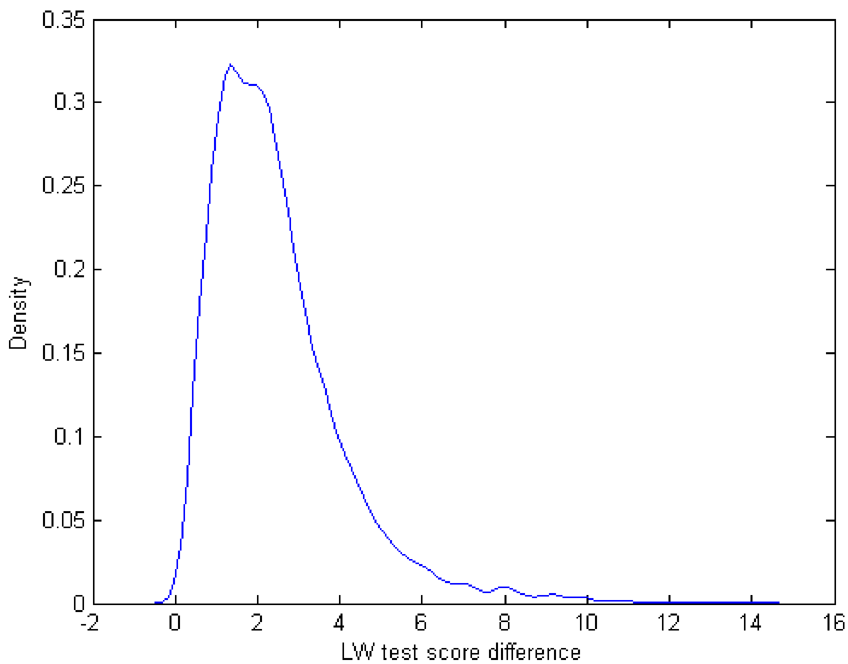
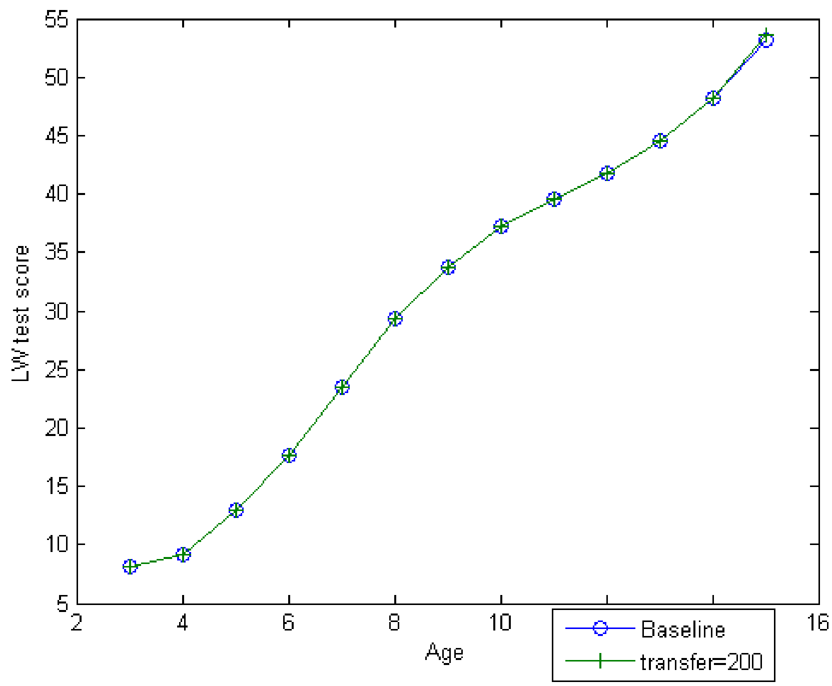


Figure 15: Average Child's Test Scores



Note: In the baseline I draw the income value from the data. For the treatment group I give weekly transfer of $200.

B Tables

Table 1: Data Sample

	Used variable from the data	Years	Source
h_t	Mother years of school	1997,2002,2007	PSID
b_t	Annual family income	1997,2002,2007	PSID
θ_t	Letter-Word score	1997,2002,2007	CDS
$Time_t^p$	Total active time parents spend with child	1997,2002,2007	CDS
$Time_t^c$	Total time that child spend at school study alone	1997,2002,2007	CDS

Notes: write note here

Table 2: Summary statistics

Variable	**Mean**	**Std. Dev.**	**N**
Family income ($/week)	951.55	623.08	3579
LW Test Score	34.29	16.35	1383
Total time on education (hours/week)	30.88	16.04	1272
Parents' active time with child (hours/week)	23.51	15.49	1272
Ozone design value	6.12	0.87	2139

Notes: write note here

Table 3: Summary Statistics for sample at 1997

Variable	**Mean**	**Std. Dev.**	**N**
Mothers education	13.96	1.93	750
Family size	2.19	0.89	751
Mothers age at first birth	24.31	5.68	751

Notes: write note here

Table 4: Estimated Parameters

Parameter	Description	Estimate	SE
α_1	Consumption impact	.26	.01
α_2	Parents leisure impact	.20	.02
α_3	Child leisure impact	.19	.03
α_4	Child's human capital impact	.35	.01
p_1	Expenditure parameter	.018	.00
p_2	Expenditure intercept parameter	28.42	8.26
φ	Child's human capital multiplier at final period	.50	.05

Table 5: Sample Fit for Time Investment

Age Category	Parents time with child (hr/week)		Childs time on education alone (hr/week)	
	Data	Simulated	Data	Simulated
3-6	34.92	31.34	18.56	21.52
7-10	23.39	19.69	30.48	30.54
11-15	18.29	8.87	34.01	31.52

Table 6: Sample Fit for Letter-Word Test Scores

Age Category	Letter-Word Test Scores	
	Data	Simulated
3-6	9.35	14.78
7-10	32.53	30.13
11-15	45.77	45.76

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