Intergenerational Long Term Effects of Preschool - Structural Estimates from a Discrete Dynamic Programming Model *

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Abstract

Using the NLSY79 (National Longitudinal Study of Youths, 1979) and the NLSY79 Children and Young Adults datasets, this paper formulates and then empirically estimates an altruistic model of parental preschool investment within a structural dynamic programming framework. The paper provides conditions for identification of the structural parameters of the dynamic programming model and carries out a Lucas-Critique free policy analysis using the estimated structural parameters. The paper empirically estimates the production processes for various measures of cognitive and non-cognitive skills of a child and the role that the parental preschool investment plays in such production processes. It then examines the effect of a publicly provided preschool policy to disadvantaged children on their educational and labor market achievements, and also on the intergenerational long-term effect on social mobility, college mobility, and earnings inequality. The paper calculates the tax burden of such a social contract policy, taking into account these intra- and inter-generational effects.

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1 Introduction

We formulate an altruistic model of parental preschool investment within a structural stochastic dynamic programming framework. The structural parameters of a structural dynamic programming model are, in general, not all statistically identified (see Hansen and Sargent [1981], and Rust [1994]). If some parameters are not identified, the estimation of these parameters using the maximum likelihood estimation procedure or any other optimizing procedures may cause serious computational problems. Moreover, the policy analysis based on unidentified parameter estimates is of very little content. In this paper we provide conditions for parametric and non-parametric identification of our structural dynamic programming model, estimate the structural parameters using the maximum likelihood estimation procedure, and then use these estimated parameters to examine the effect of preschool on the production of cognitive and non-cognitive skills of children, their effects on school and labor market achievements, and the intergenerational long-term effects on social mobility, schooling mobility and earnings inequality.

In the past three decades in the US the income gap between the rich and the poor and the wage gap between the college educated and the non-college educated workers have been widening. Equalizing education has remained as the main policy in the US to reduce poverty and income disparities. Many are, however, highly skeptical about a positive answer to the basic question: "*Can we conquer poverty through school?*"

There are many reasons for this skepticism. In the US, education up to high school level is virtually free. Yet many children of poor SES do not complete high school and many of them perform poorly in schools. This naturally beckons to the possibility that the poor quality of the public schools that the children of poor SES attend is the reason for such failings. Improving school quality will improve school performance of these children only marginally. Many empirical studies find that better school quality in terms of lower class size, higher public expenditures per pupil, improved curriculum, and higher desegregation have only marginal effects on school performance of the children of poor SES. See Hanushek [1986] for a survey of the studies along this line.

A growing consensus reached among educators, among media writers (see for instance, Taub [2002]), among researchers in economics (see for instance, Heckman [2000] and Currie [2001], Cunha, Heckman, Lochner and Masterov [2006]) and among researchers in sociology, psychology and education (see for in stance, Barnett [1995], Entwisle [1995], McCormick [1989], Schweinhart et al. [1993]) that children of poor SES are not prepared for college because they were not prepared for school to begin with. The most effective intervention for the children of poor SES should be directed at the preschool stage so that these children are prepared for school and college. The question is then does preschool has long-term positive effects on school performance and labor market success? This is the main issue that we address in this paper.

There are two types of quantitative studies on this issue. One set of studies use data on high cost high quality pilot preschool programs such as the High Scope/Perry Preschool Program and the North Carolina Abecedarian Study. These studies find a substantial lasting effect of these programs on school performance and labor market outcomes. The participants in these programs are, however, a very small in number and are not representative of the US population.

The other set of studies use data on the Head Start preschool program which is funded by the Federal government. It is available to the children whose parents earn incomes below poverty line. Not all eligible children are, however, covered by the program. The quality of the program is very poor compared to the above mentioned pilot programs or most private preschool programs. Some studies find that the Head Start Preschool Program has no long-term effect on children's cognitive achievements and school performance, especially for black children. Currie and Thomas [1995] carry out a careful econometric investigation and conclude that the benefits disappear for black children because most of the Head Start black children attend low quality public schools. But after controlling for the school quality, they find significant positive effects of Head Start Preschool Program. See Barnett [1995] for a survey of other studies on the long-term school effect of early childhood programs.

The above studies are not based on nationally representative samples of children, and most studies examine only the effect on school performance such as grade retention and high school and college graduation rates, and do not model parental choice of investing in their children's preschool. In this paper, we formulate a model of parental investment in preschool that is guided by economic incentives. We show that preschool benefits children in acquiring many useful cognitive and non-cognitive skills, especially for the children of poor SES who live in poor HOME environments. We also show the importance of non-cognitive skills in improving school performance and life-time earnings of children, after controlling for their education level, innate ability, and family background. Heckman and Rubinstein [2001] used data on GED testing program in the US, after careful econometric analysis they show that non-cognitive skills are important determinant of earnings and educational attainment.

The rest of the paper is organized as follows. Section 2 provides the basic decision making framework. Section 3 defines notations of the paper. Section 4 develops the intergenerational altruism model of parental preschool investment within a structural dynamic programming framework. Section 5 deals with the issues related to identification of the structural parameters of the dynamic programming model. Section 6 describes the estimation algorithm that we use. Section 7 provides the empirical specifications of the production processes of cognitive and non-cognitive skills and reports the parameter estimates. Section 8 carries out policy analysis. Section 9 concludes the paper.

2 The Basic Framework

In this section we formulate an econometrically implementable model of preschool investment decision of an altruistic parent in a dynamic programming framework. The preschool investment decision of a parent depends on several other decisions at later stages of a child's life. While we describe each of these decision stages for a better understanding of our framework and for future work, in this paper, however, we restrict only to preschool investment decision, taking all other decisions as exogenously given. We treat each parent-child pair as independent. We assume parthenogenetic mode of biological reproduction in our model and with due respect to both genders, we address all individuals in male gender.

2.1 Individual Decision Problem

We assume that an individual's life comprises of several discrete periods during which important life-cycle events relevant to leaning and earning occur. While it may be more realistic to have finer divisions of these periods, for analytical tractability and given data limitations, we aggregate the whole life-cycle into four periods: [0-5), [5-17), [17-26), [26--]. In each of these periods some educational and labor market decisions are made and outcomes are observed.

During ages [0-5), a parent invests in his child's preschool activities which develop the child's school readiness, and various cognitive and non-cognitive skills. Let a denote the parental preschool investment decision. At the end of the preschool period, the child acquires a level of innate ability or cognitive skill τ, social skill σ, motivational skill μ, self-esteem skill, η, and internal self-control skill ϕ. The levels of these skills that a child develop depend on various other childhood interventions, for instance, on the child-rearing practices at home, the nature of neighborhood and home environments in which the child grows up (see Mohanty and Raut[2009] for more on this), and the level of schooling, cognitive, socialization and motivational skills of the parent. We do not, however, explicitly include these additional determinants of skill formation in this paper to keep computations manageable.

During ages [5-17), the child goes to school. The school performance at this stage depends on his level of τ, σ, μ, η, and ϕ that the child has acquired during the previous stage, on the quality of the school that he attends[1], and the type of neighborhood kids whom the child mingles with. It also depends on the parental home inputs such as how many hours the parent spend time with the child to do his homework, how many hours the child watches TV, and how stable and stimulating the relationships among the family members are. Many of these are choice variables for the parent. We do not have adequate information about these factors in our dataset, so we do not include them.

During ages [17-26), the child decides whether to complete college education or not, which depends on his parent's income, his learned and innate abilities. We take this decision as exogenously given, and denote it as the function $s(\tau, \sigma, \mu, \eta, \phi, s, \varepsilon_s)$, where ε_s represents the random events during the life-cycle of the child that affect his schooling decision.

During ages [26-], he works, forms his family, has one child and decides how much to invest in his child's preschool. We assume that apart from the level of schooling, and other cognitive and non-cognitive skills, there are other life cycle events and variation in tastes that affect individual's choices. We bundle all these unobserved sources of heterogeneity among individuals into a vector of random variables ε. The state variables of our system are represented by the vector $z = (\tau, \sigma, \mu, \eta, \phi, s, \varepsilon)$. We denote the observable components of the state variable by $x = (\tau, \sigma, \mu, \eta, \phi, s)$ and use the notation $z = (x, \varepsilon)$. For any variable w, we adopt the convention of using w if it refers to a parent and w' if it refers to his child.

We assume that given his parental preschool investment decision a, and a realization of his parent's state variables $z = (x, \varepsilon)$, the components of a child's state variable $z' = (x', \varepsilon')$, where $x' = (\tau', \sigma', \mu', \eta', \varphi')$, and ε' are generated stochastically by the following

[1] See Nishimura and Raut (2007) for a model of parental choice of school quality in an altruistic dynamic programming framework and its effect on social mobility and intergenerational poverty trap.

conditional probability density functions:

$$
\begin{gathered}
q_\tau \left(d\tau' | \tau, s, a\right) \\
q_\sigma \left(d\sigma' | \tau', \tau, \sigma, \mu, s, a\right) \\
q_\mu \left(d\mu' | \tau', \tau, \sigma, \mu, s, a\right) \\
q_\eta \left(d\eta' | \tau', \tau, \sigma, \mu, s, a\right) \\
q_\varphi \left(d\varphi' | \tau', \tau, \sigma, \mu, s, a\right) \\
q_s \left(ds' | \tau', \sigma', \mu', s, a\right) \\
g \left(d\varepsilon' | \tau', \sigma', \mu', s'\right)
\end{gathered} \tag{1}
$$

In the above specifications of the conditional probabilities, the conditioning variables conform to what we know in the child development literature about the production processes of these state variables. We will discuss the details of each production process in section 7.2. Given the density functions in Eq. (1), the transition probability density $p\left(dx', d\varepsilon' | x, \varepsilon, a\right)$ over the states of our system is determined.

We assume that the lifetime average annualized permanent earnings of an individual with the state variable (x, ε) is represented by an earning function $w\left(x, \varepsilon\right)$. Let A be the set of all possible preschool investment choices of a parent. We assume it to be an ordered set. Assume that the annualized average cost to parent of making a preschool investment choice a is $\theta\left(a\right), a \in A$. Given his choice a and permanent annualized income w, the annualized permanent consumption $c\left(w, a\right)$ is then given by $c\left(w, a\right) \equiv w - \theta\left(a\right)$.The choices of a parent with observable characteristics x are restricted to the set $A\left(x, \varepsilon\right) \equiv \left\{a \in A | c\left(w\left(x, \varepsilon\right), a\right) > 0\right\}$. The choice a yields direct utility from life-time annualized consumption and indirect utility through its effect on child outcome and welfare, as represented in the following Bellman equation corresponding to the parent's preschool investment decision problem

$$
V\left(x, \varepsilon\right) = \max_{a \in A(x,\varepsilon)} u\left(x, \varepsilon, a\right) + \beta \int V\left(x', \varepsilon'\right) p\left(dx', d\varepsilon' | x, \varepsilon, a\right) \tag{2}
$$

where $V(.)$ is the intergenerational welfare function, known in the dynamic programming literature as the value function, $u(.)$ is the felicity index of yearly permanent consumption over the whole lifetime of the parent, and the parameter β measures the degree of parental altruism toward the child.

Under general regularity conditions on $u(.)$, $p\left(dx', d\varepsilon' | x, \varepsilon, a\right)$ and β, the value function $V\left(x, \varepsilon\right)$, and a measurable optimal decision rule $a^*\left(x, \varepsilon\right)$ exists (see, for instance, Bhattacharya and Majumdar [1989, Theorem 3.2]). Given $u(.)$, $p\left(dx', d\varepsilon' | x, \varepsilon, a\right)$ and β, satisfying the regularity conditions, we carry out a Lucas-Critique free policy evaluation by examining a policy's effect on the individual optimal decision a on the intergenerational welfare level V, and we also examine the intergenerational long-run aggregate effect of the policy on the economy by aggregating individual choices with respect to the long-run population distribution, also known as the invariant population distribution, of the equilibrium transition probability distribution $p\left(dx', d\varepsilon' | x, \varepsilon, a^*\left(x, \varepsilon\right)\right)$.

To be able to do this, we need to estimate the structural parameters. Our data consists of a sample of parent-child pairs with information on parent's observable state x, child's observable state x', parent's permanent income w, and the parent's preschool investment decision a. Suppose a vector of parameters ξ_p specifies the probability distributions in Eq. (1), i.e., given ξ_p, the transition probability distribution $p\left(dx', d\varepsilon' | x, \varepsilon, a\right)$ is determined. Our problem is then to statistically estimate the structural parameters $\zeta = \left\{u(.), \xi_p, \beta\right\}$ given observable information on a random sample of parent-child pairs $y = \{(x_i, x_i'), a_i\}_{i=1}^n$ such that the predicted behaviors of the sample from the model are close to observed behavior. We denote the log-likelihood function of the sample by $\mathcal{L}_y(\zeta)$. Estimation of the model involves two steps: For a given ζ, calculate the probability distribution of the endogenous variables $a_i | x_i$ and $x_i' | x_i, a_i$ using the model to form the log-likelihood of the sample $\mathcal{L}_y(\zeta)$ and then use an appropriate estimation procedure to choose a ζ.

Two questions need be addressed to that end. First, is the computation of the likelihood $\mathcal{L}_y(\zeta)$, which involves solving the dynamic programming problem in Eq. (2) repeatedly for each (x, ε), feasible with the currently available computing technology, especially when ε is a continuous multivariate random variable? Second, are the structural parameters of the model identified (the definition of identification is stated later)?

The answer to both questions is in general no. Following the literature, we make simplifying assumptions to transform the above structural dynamic programming problem into a random utility model of discrete choices. We will show that these assumptions greatly simplify the computation and the identification of the structural parameters of the model. Given those assumptions, we will see two facts: First, the set of structural parameters ξ_p determines the transition distribution $p\left(x' | x, a\right)$ of the observable state variables, which is the mixture distribution of the original transition probability distribution, more specifically $p\left(x' | x, a\right) = \int p\left(x', \varepsilon' | x, \varepsilon, a\right) \, d\varepsilon | x \, d\varepsilon' | x'$. Second, the set of optimal choice probabilities $P\left(a | x\right), a \in A\left(x\right), x \in X$ over the observed discrete choices depends on ξ_p only through $p\left(x' | x, a\right)$.

Notice that the optimal choice a is treated as an exogenous variable in the estimation of $p\left(x'|x,a\right)$, the maximization of joint likelihood of two components is more efficient. To make estimation task computationally manageable, however, again following the trend in the literature, in place of ξ_p, we take an estimate of $p\left(x'|x,a\right)$ as our fixed parameters in the vector of parameters ζ, and in place of β, we calibrate β from other studies, and then form the likelihood of the sample of observed discrete choices $a_i|x_i$ for identification and estimation of the remaining parameters.

3 Notations

In the rest of the paper, our parameter vector is $\zeta = \{u\left(x,a\right), p\left(x'|x,a\right), \beta\}, a \in A\left(x\right), x \in X$ where $p\left(x'|x,a\right)$ and β are fixed. Denote by Ξ the set of all such parameter values. We denote by $\mathcal{L}_y(\zeta)$ the log-likelihood of the sample of observed choices $y = \{a_i|x_i, i = 1...n\}$. Given a set of conditional choice probabilities $\{P\left(a|x\right), a \in A\left(x\right), x \in X\}$ which depends on ζ, the log-likelihood function $\mathcal{L}_y(\zeta)$ of the sample is defined.

Let J_x denote the number of elements in the feasible choice set $A\left(x\right)$. Denote by $J = \sum_{x\in X} J_x$. Assume that X is a finite ordered set of M elements.

Denote by $F\left(a\right) = \left[f\left(x'|x,a\right)\right]_{x',x\in X}$ the $J_x \times J_{x'}$ conditional transition probability matrix given a choice $a \in A\left(x\right)$ where the element $f\left(x'|x,a\right)$ corresponding to the row x and the column x' is the probability of the child moving to state x' given that his parent is from the state x and he had made a choice $a \in A\left(x\right)$. We denote by $F\left(x,a\right)$ the row vector of $F(a)$ corresponding to the parent's state x.

The vector of conditional choice probabilities denoted by $\mathcal{P} = \{P\left(a|x\right), a \in A\left(x\right), x \in X\}$ is ordered by the primary index of ordering in X and the secondary index of the ordering in A. For each x, the component vector of conditional choice probabilities $\{P\left(a|x\right), a \in A\left(x\right)\}$ belongs to a $J_x - 1$ dimensional simplex. The set of all vectors $\mathcal{P}$ of conditional choice probabilities $\triangle$ is a subset of $\Re^{MJ}_{++}$ which is restricted to the interior of the M-fold cross product of the $J_x - 1$ dimensional simplices.

For any function $v\left(x,a\right)$, its vector representation is a $J \times 1$ vector v (i.e., with the same symbol v) in which the function values $v\left(x,a\right)$'s are ordered in the same way as in $\mathcal{P}$. For any scalar or a vector function $w\left(x\right)$, we denote by w (again using the same symbol w to denote it) the values of w stacked in rows in the same order as in the ordered set X.

For any random vector or a random variable $w\left(x,a\right)$, we denote its expectation with respect to a by $\bar{w}\left(x\right)$, i.e., $\bar{w}\left(x\right) \equiv \sum_{a\in A(x)} w\left(x,a\right) P\left(a|x\right)$, (with the convention that when

w is a random vector, the product inside this summation is element-by-element). Define the $M \times J$ matrix Π derived from a vector of conditional choice probabilities $\mathcal{P}$ by

$$\underset{M\times J}{\Pi} = \begin{pmatrix} P(a=1|x_1) & \dots & P(a=J|x_1) & \dots & 0 & \dots & 0 \\ 0 & \dots & 0 & \dots & 0 & \dots & 0 \\ 0 & \dots & 0 & \dots & P(a=1|x_M) & \dots & P(a=J|x_M) \end{pmatrix}$$

and the transition matrices in matrix notation as a $J \times M$ matrix F by,

$$\underset{J\times M}{F} = \begin{pmatrix} f(x_1'|x_1, a=1) & \dots & f(x_M'|x_1, a=1) \\ & \dots & \\ f(x_1'|x_1, a=J_{x_1}) & \dots & f(x_M'|x_1, a=J_{x_1}) \\ & \dots & \\ f(x_1'|x_M, a=1) & \dots & f(x_M'|x_M, a=1) \\ & \dots & \\ f(x_1'|x_M, a=J_{x_M}) & \dots & f(x_M'|x_M, a=J_{x_M}) \end{pmatrix}$$

4 Structural Estimation

The structural estimation of the original problem is computationally intractable. Similar to Rust [1994], we make the following simplifying assumptions to transform the original model in Eq. (1) to a random utility model. In the next two sections, we utilize these simplifications to find conditions for identification and estimation of structural parameters.

We assume that $w(x,\varepsilon)$ and hence $A(x,\varepsilon)$ does not depend on ε, i.e., $w()$ does not contain any unobservable idiosyncratic shocks. However, we assume that ε represents a taste shifter for individual preferences and constitutes our only source of unobserved heterogeneity, the specific nature of which is stated formally in the following assumption.

Assumption 1 *$u(x,\varepsilon,a) = u(x,a) + \varepsilon(a)$, and support of $\varepsilon(a)$ is the real line for all $a \in A(x)$.*

We also make the following additional assumptions.

Assumption 2 *The transition probability $p(x',\varepsilon'|x,\varepsilon,a) = g(\varepsilon'|x') f(x'|x,a)$ for some twice continuously differentiable density function g with finite first moment.*

Assumption 3 *The set of observable individual characteristics $X = \{x^1, ..x^M\}$ is a finite ordered set.*

Under assumptions 1 - 3 , we have

$$V(x,\varepsilon) = \max_{a\in A(x)} u(x,a) + \varepsilon(a) + \beta \sum_{x'\in X} \int V(x',\varepsilon')\, g(d\varepsilon'|x')\, f(x'|x,a) \tag{3}$$

Denote the value function, after integrating out the unobservable component of the state variable, by $v(x) \equiv \int V(x,\varepsilon)\, g(d\varepsilon|x)$. Integrating both sides of Equation (3) with respect to the conditional density $g(d\varepsilon|x)$, and utilizing this notation for $v(x)$, we have

$$v(x) = \int \max_{a\in A} [\tilde{v}(x,a) + \varepsilon(a)]\, g(d\varepsilon|x) \tag{4}$$

where

$$\begin{aligned} \tilde{v}(x,a) &\equiv u(x,a) + \beta \sum_{x'\in X} v(x')\, f(x'|x,a) \\ &= u(x,a) + \beta F(x,a).v \end{aligned} \tag{5}$$

Eq. (4) above is a random utility model in which the function $\tilde{v}(x,a)$ measures the common utility that an individual of observable characteristics x derives from a choice $a \in A(x)$. Denote by

$$\Omega(x,a) = \left\{\varepsilon|\tilde{v}(x,a) + \varepsilon(a) \geq \tilde{v}(x,a') + \varepsilon(a'), \text{for all } a' \in A(x)\right\} \tag{6}$$

the set of individuals with observed characteristics x who made a as their optimal choice. The conditional choice probabilities are then given by

$$P(a|x) = \int_{\Omega(x,a)} g(d\varepsilon|x). \tag{7}$$

By partitioning the domain of integral in Eq. (4) into disjoint regions $\Omega(x,a), a \in A(x), x \in X$ and then integrating we have the following,

$$\begin{aligned} v(x) &= \sum_{a\in A(x)} P(a|x) \left[u(x,a) + \frac{\int_{\Omega(x,a)} \varepsilon(a)\, g(d\varepsilon|x)}{P(a|x)} + \beta \sum_{x'\in X} v(x')\, f(x'|x,a) \right] \\ &= \sum_{a\in A(x)} P(a|x) [u(x,a) + e(x,a) + \beta F(x,a)\cdot v] \text{ ...(*)} \\ &= \bar{u}(x) + \bar{e}(x) + \beta \bar{F}(x) \cdot v \end{aligned} \tag{8}$$

where

$$e(x,a) \equiv \int_{\Omega(x,a)} \varepsilon(a)\, g(d\varepsilon|x) / P(a|x) \tag{9}$$

in line (*) is the conditional expectation of the component $\varepsilon(a)$ of the random vector ε given x and a. Writing the above in matrix notation, we have

$$v = \bar{u} + \bar{e} + \beta \bar{F} \cdot v \equiv \Phi(v, \zeta) \tag{10}$$

Let $v(\zeta)$ be a fixed point of the map $\Phi(v, \zeta)$ for given $\zeta \in \Xi$, and denote by $\mathcal{P}(v)$ the conditional choice probabilities in Eq. (7) for a given value function v. Then the computation of the likelihood of the sample is simplified to the computation of the fixed point of the above map $\Phi(v, \zeta)$. The computation of $P(a|x)$, and $e(x, a)$ involve multi-dimensional numerical integration, which may make computations extremely slow. Both computational tasks are, however, substantially simplified under the following assumption:

Assumption 4 *The components of ε are independently and identically distributed as extreme value distribution with location parameter 0 and scale parameter 1.*

McFadden (1981) has shown that under Assumption 4, $e(x, a) = (\lambda - \ln P(a|x))$, where λ is the Euler-Mascheroni constant, with a numerical value of $\lambda = 0.57721566$, and the conditional choice probability $P(a|x)$ has the following Logit representation,

$$P(a|x) = \frac{e^{\tilde{v}(x,a)}}{\sum_{a \in D} e^{\tilde{v}(x,a')}} \tag{11}$$

The above strategy of computational simplification was pioneered by Rust [1987]. The computational burdens could be, however, further simplified as follows: From Eq. (10) it follows that $v = \left[I_M - \beta \bar{F}\right]^{-1} [\bar{u} + \bar{e}]$. Substituting this in Eq. (5), we have

$$\tilde{v}(x, a) = u(x, a) + \beta F(x, a) \left[I_M - \beta \bar{F}\right]^{-1} [\bar{u} + \bar{e}] \tag{12}$$

It is easy to see that given $\mathcal{P}_0 \in \triangle$, the right hand side of the above, and hence, a new vector of conditional choice probabilities say $\mathcal{P}_1 \in \triangle$ can easily be computed by substituting it in Eq. (11). We represent this relationship for each structural parameter $\zeta \in \Xi$ by $\mathcal{P}_1 = \Psi(\mathcal{P}_0, \zeta)$. Following the line of argument in Aguirregabiria and Mira (2002), it is easy to show that for each $\zeta \in \Xi$, there exists a unique fixed point $\mathcal{P}(\zeta)$ to the mapping $\Psi(\mathcal{P}, \zeta)$, and starting from any initial $\mathcal{P}_0 \in \triangle$, the iterative process $\mathcal{P}_{n+1} = \Psi(\mathcal{P}_n, \zeta)$, $n \geq 0$ converges to the fixed point $\mathcal{P}(\zeta) \in \triangle$. Thus, for each structural parameter $\zeta \in \Xi$, there exists a unique likelihood of the sample $\mathcal{L}_y(\zeta)$, the computation of which is brought down to computation of the fixed point of the mapping Ψ on the finite dimensional space $\triangle$.

5 Identification of Structural Parameters

In the previous section we saw that given $\zeta \in \Xi$, there exists a unique likelihood function $\mathcal{L}_y(\zeta)$. To be able to estimate $\zeta \in \Xi$, the model should be identified in the sense that

$$\mathcal{L}_y(\zeta) = \mathcal{L}_y(\zeta') \; a.e. \text{ if and only if } \zeta = \zeta', \tag{13}$$

the a.e. is with respect to the dominant probability measure defining the likelihood of the sample. Following Prakasa Rao (1992), we say that our model is *globally identified* if the relationship in Eq. (13) holds for any two $\zeta, \zeta' \in \Xi$, and is *locally identified* around a particular parameter $\zeta \in \Xi$, if the relationship in Eq. (13) holds for all $\zeta' \in \Xi$ in a neighborhood of ζ.

To find reasonable conditions for identification, from Eq. (6) note that the optimal choices are invariant if we add a location m_x and divide both sides by a scale factor $\sigma_x > 0$, for each $x \in X$. Thus it follows that we can recover the utility function only up to a scale and location. Given this fact, we restrict the one period utility function $(u(x,a), a \in A(x))$ to lie in a $J_x - 1$ dimensional open submanifold of $\Re^{J_x}$ for each $x \in X$. We take each possible utility vector $(u(x,a), a \in A(x), x \in X)$ to lie in the cross product (or equivalently in the direct sum, if we view $\Re^{J_x}$ to be embedded in $\Re^{J}$) of these $J_x - 1$ dimensional submanifolds over all $x \in X$. There are many such manifolds, and up to diffeomorphisms they are all equivalent. We define one such manifold $\mathcal{U}$ using the map $\varphi : \triangle \ni \mathcal{P} \mapsto u \in \Re^{J}$ (which reads as, φ takes a member $\mathcal{P}$ in $\triangle$ to a member u in $\Re^{J}$) by

$$u = \left[I_J + \beta F \left(I_M - \beta \bar{F} \right)^{-1} \Pi \right]^{-1} \left[\tilde{v} - \tilde{e} \right] \equiv \varphi(\mathcal{P}) \tag{14}$$

where $\tilde{v}(x,a) = \ln P(a|x)$ and $\tilde{e} = \beta F \left(I_M - \beta \bar{F} \right)^{-1} \Pi e$. Take $\mathcal{U} = \varphi^{-1}(\triangle)$. It can be shown that the set $\mathcal{U}$ is a $J - M$ dimensional smooth manifold. Given parameters β, and F fixed, we restrict our parameter space Ξ to be such that the u-component of a parameter vector $\zeta \in \Xi$ is restricted to lie in $\mathcal{U}$. The most general non-parametric family that we can restrict our parameters u to lie in is $\mathcal{U}$. Our nonparametric identification issue boils down to the question, under what conditions can we identify our structural model in this non-parametric family of $\mathcal{U}$? Theorem 1 addresses this, using the following assumption

Assumption 5 *Given the vector of transition probabilities F, the degree of altruism parameter β is such that (1) $0 \leq \beta < 1$ and (2) $I_J + \beta F \left(I_M - \beta \bar{F} \right)^{-1} \Pi$ is of full rank.*

Note that there always exist such $\beta' s$ at least near $\beta = 0$. Also note that $\beta = 1$ will violate condition (2) since in that case $I_M - \beta\bar{F}$ is not invertible, as each row will add-up to zero.

Theorem 1 (Nonparametric Identification) *Suppose the components β and F of the parameter vectors are fixed. Let $\mathcal{P} \in \triangle$ be a vector of conditional choice probabilities that satisfy Assumption 5. Then there exists a unique utility function $(u(x,a), a \in A(x), x \in X) \in \mathcal{U}$ that generates $\mathcal{P}$ as the optimal solution to the choice problem in Eq. (2). Furthermore, the model in Eq. (2) is globally or locally non-parametrically identified depending on whether Assumption 5 holds globally or locally.*

Proof. Let $\mathcal{P} \in \triangle$ be a vector of conditional choice probabilities that satisfy Assumption 5. Note that writing Eq. (12) in matrix notation, we have $\tilde{v} = \left[I_J + \beta F\left(I_M - \beta\bar{F}\right)^{-1}\Pi\right]u + \beta F\left(I_M - \beta\bar{F}\right)^{-1}\Pi e$, where $\bar{F}$ is the expectation of $F(a)$ with respect to $\mathcal{P}$. Taking $\tilde{v}(x,a) \equiv \ln P(a|x)$, and denoting by $\tilde{e} = \beta F\left(I_M - \beta\bar{F}\right)^{-1}\Pi e$, we have

$$u = \left[I_J + \beta F\left(I_M - \beta\bar{F}\right)^{-1}\Pi\right]^{-1}\left[\tilde{v} - \tilde{e}\right] \tag{15}$$

Thus by Assumption 5, for each $\mathcal{P}$, there exists a unique $u \in \mathcal{U}$.

We now prove the second part regarding the nonparametric identification. Note that the data on distribution of choices given a fixed number of individuals $n(x)$ (a positive integer) for each observed value of individual characteristics $x \in X$ can be summarized as an ordered vector y defined similar to $\mathcal{P}$ by $y = (n(a|x), a \in A(x), x \in X)$ where $n(a|x)$ is the number of individuals who chose $a \in A(x)$ given their characteristics $x \in X$. The likelihood of the sample can be written as follows

$$\begin{aligned}
L_y(\mathcal{P}) &= \prod_{x\in X}\frac{n(x)!}{\prod_{a\in A(x)} n_a(x)!}\exp\left(\sum_{x\in X} n(x)\ln\left(1 - \sum_{a=1}^{J_x-1} P(a|x)\right)\right)\times \\
&\quad \exp\left(\sum_{x\in X}\sum_{a=1}^{J_x-1} n(a|x)\ln\left(\frac{P(a|x)}{1-\sum_{a=1}^{J_x-1}P(a|x)}\right)\right) \\
&= h(y)\,g(\eta)\exp\left(y'\eta\right), \text{ where } \eta = (\eta(a|x), a \in A(x), x \in X), \text{with} \\
\eta(a|x) &= \ln\left(\frac{P(a|x)}{1-\sum_{a=1}^{J_x-1}P(a|x)}\right), \text{and } g(\eta) = -\sum n(x)\ln\left(1 + \sum_{a=1}^{J_x-1}\exp\eta(a|x)\right),
\end{aligned}$$

and $h(y)$ is the multiplicative component in the first expression. It follows from the above that $L_y(\mathcal{P})$ is an exponential distribution. The determinant $\det(\mathfrak{I}(\mathcal{P}))$ of the Fisher information matrix $\mathfrak{I}(\mathcal{P})$ of $L_y(\mathcal{P})$ at any parameter vector $\mathcal{P} \in \triangle$ can be shown to be

$\det(\Im(\mathcal{P})) = \left[\prod_{x\in X}\prod_{a=1}^{J_x-1} P(a|x)\right]^{-1}$, which is always > 0 since each $P(a|x) > 0$. Since $\det(\Im(\mathcal{P}))$ is a continuous function of $\mathcal{P}$, there exists a neighborhood of $\mathcal{P}$ in $\triangle$ such that the Fisher information matrix is of full rank for all $\mathcal{P}$ in that neighborhood. Moreover, note that the function $g(\eta)$ is continuously differentiable in η. Hence by Prakash Rao [1992, Theorem 6.3.2], for any $\mathcal{P}'$ in a neighborhood of $\mathcal{P}$, we have $L_y(\mathcal{P}) = L_y(\mathcal{P}')$ *a.e.* $\Leftrightarrow$ $\mathcal{P} = \mathcal{P}'$. But $u = \varphi(\mathcal{P})$ in Eq. (14) is a 1-1 function from $\triangle$ to $\mathcal{U}$ around $\mathcal{P} \in \triangle$ that satisfies Assumption 5. Hence for any $\zeta \in \Xi$ such that the corresponding $\mathcal{P}(\zeta)$ satisfies Assumption 5, there exists a neighborhood of ζ in Ξ such that for any ζ' in that neighborhood, $L_y(\mathcal{P}(\zeta)) = L_y(\mathcal{P}(\zeta'))$ *a.e.* $\Leftrightarrow \zeta = \zeta'$. Hence the model in Eq. (2) is locally nonparametrically identified around a ζ whose associated $\mathcal{P}(\zeta)$ satisfies Assumption 5. It is also clear that if Assumption 5 is true for all $\mathcal{P} \in \triangle$, the model in Eq. (2) is also globally identified. ■

The conditional choice probabilities $\mathcal{P} = \{P(a|x), a \in A, x \in X\}$ are nothing but the aggregate demand functions of discrete choices $a \in A$ as a function of individual characteristics $x \in X$. The characteristics $x \in X$ is acting like a price of the Marshallian demand function. Nonparametric identification problem in our set-up can be viewed as the well-known aggregation problem of the consumer theory: *Given a system of demand functions $P \in \triangle$, when does there exist a utility function $u(x,a)$ that generates P as the optimal solution of problem in Eq. (2)*? The above theorem provides conditions for an analogous aggregation problem in the present context of structural dynamic programming problem.

Suppose instead of most general non-parametric utility specifications for the parameter vector ζ, we parametrize u (and also possibly β, but F is still assumed to be fixed) to have a parametric form $\zeta : \Theta \to \Xi$, where $\Theta \subset \Re^k$, $k < J - M + 1$ is an open set. When can we identify such parametric models? To state our sufficient condition for this, we recall a definition from the Differential Geometry. A map $f : \Theta \to \triangle$ is an *immersion* at $\theta \in \Theta$, an open subset of $\Re^k$, if the differential map $df_\theta : \Re^k \to T_{f(\theta)}(\triangle)$ is injective, i.e., one-to-one, where $T_{f(\theta)}(\triangle)$ is the tangent space of the manifold $\triangle$ at $f(\theta)$.

Theorem 2 (Parametric Identification) *Let $\Theta \subset \Re^k$ be an open set. Let $\zeta : \Theta \to \Xi$ denotes a family of parametric models. A parametric model is locally identified at $\theta \in \Theta$ if and only if the map $\mathcal{P}(\zeta(\theta)) : \Theta \to \triangle$ is an immersion at θ. The parametric model is globally identified if and only if the map $\mathcal{P}(\zeta(\theta))$ is an injective map.*

Proof. Since$\mathcal{P}(\zeta(\theta))$ is an immersion at θ, there exists a neighborhood around θ in Θ such that $\mathcal{P}(\zeta(\theta))$ is one-one in this neighborhood. For any θ' in this neighborhood of θ,

$\mathcal{L}_y\left(\mathcal{P}\left(\zeta\left(\theta\right)\right)\right) = \mathcal{L}_y\left(\mathcal{P}\left(\zeta\left(\theta'\right)\right)\right)$ a.e. implies $\mathcal{P}\left(\zeta\left(\theta\right)\right) = \mathcal{P}\left(\zeta\left(\theta'\right)\right)$ since $\mathcal{L}_y\left(\mathcal{P}\right)$ is globally identified in the parameter space $\triangle$ by theorem 1. Hence $\theta = \theta'$ since $\mathcal{P}\left(\zeta\left(\theta\right)\right)$ is 1-1 in this neighborhood. The second part follows immediately. ■

6 Econometric implementation

The structural estimation of discrete dynamic programming models has two components. One component involves solving a fixed point problem associated with the dynamic programming problem to compute the likelihood function of the sample, and the second component involves finding a set of structural parameters to maximize the likelihood of the sample. Rust (1987) used a fixed point algorithm on value function, and then used the value function to compute the optimal choice probabilities for each set of structural parameters. Whereas, Hotz and Miller (1993) used the fixed point algorithm on the choice probabilities and then used these choice probabilities to compute the value function. Both procedures then carried the likelihood maximization to find an estimate of the structural parameters. Aguirregabiria and Mira (2002) introduced a faster estimation procedure by interchanging the order of executing these two components of the computation. They showed that their estimation procedure has good asymptotic properties. Our estimation procedure follows the Aguirregabiria and Mira procedure which can be briefly described as follows: First we compute F, the transition probability matrix, from the subset of the data of the type $\left(x_i, x_i'\right)$ of the observable states for all parent-child pairs. We then assume a parametric form of the utility function $u_\theta\left(x, a\right)$, where $\theta \in \Re^k$ and follow these steps:

1. Start with an initial $J \times 1$ vector of probabilities $\mathcal{P}_0 \in \triangle$.

2. Maximize the likelihood $\mathcal{L}\left(\theta; \mathcal{P}_0\right) = \prod_{i=1}^{n} P_0\left(a_i | x_i, \theta\right)$, where

$$\begin{aligned} P\left(a_i | x_i, \theta\right) &= \frac{e^{\tilde{v}(x,a;\theta)}}{\sum_{a \in D} e^{\tilde{v}(x,a';\theta)}} \\ \tilde{v}\left(x, a\right) &= u_\theta\left(x, a\right) + \beta F\left(x, a\right)\left[I_M - \beta \bar{F}\right]^{-1}\left[\bar{u}_\theta + \bar{e}\right] \end{aligned}$$

3. Given θ^* in step 2, compute $\mathcal{P}_1 = \left(P\left(a | x, \theta^*\right), x \in X, a \in A\right) \in \triangle$ from the above formula.

4. If $||\mathcal{P}_1 - \mathcal{P}_0|| < \varepsilon$ stop, else set $\mathcal{P}_0 = \mathcal{P}_1$ go to step 2.

Following Aguirregabiria and Mira (2002), we parameterize $u_\theta(x,a) = \theta_0 w(x) - \theta_1 a$, where θ_0 is the marginal utility of annualized lifetime earnings, and θ_1/θ_0 is the preschool investment cost in the unit of earnings w. Note that $u_\theta(x,a)$ is not identified, because for each $x \in X$, the ordered vector $(u_\theta(x,a), a \in A(x))$ should belong to an one dimensional subspace of $\Re^2$, in this specification u lies in a two-dimensional manifold instead. However, the parameter measuring the preschool investment cost θ_1/θ_0 is identified.

We have used the public domain Sun Java programming language to implement the above estimation procedure and for all other computational tasks.

7 Empirical Findings

7.1 The Dataset and Variables

For our analysis we use the NLSY79 dataset and the NLSY79 Children and Young Adults. The NLSY79 dataset contains a nationally representative sample of 12,686 young men and women who were 14-22 years old when they were first surveyed in 1979, i.e., these sampled individuals represent a population born in the 1950s and 1960s, and living in the United States in 1979. These individuals are interviewed annually. The dataset has records of school and labor market experiences of these individuals and also the information on their cognitive and non-cognitive traits. We, however, also need information on most of these variables for the parents of the respondents. This dataset does not have much information on respondents' parents. So we link this dataset with the NLSY79 Children and Young Adults dataset. The child survey dataset includes longitudinal assessments of each child's cognitive, attitudinal and social, motivational, academic and labor market experiences.

Two other important datasets in this area of research are the High/Scope Perry Preschool Study and the Carolina Abecedarian Project. These are small scale pilot programs with small number of participants. Data from these programs contain school performance information but the labor market outcome data is weak. While these datasets are good for studying the effect of high quality preschool program on school performance and labor market success, these datasets do not nationally representative samples, because the participants were selectively chosen. For details on the High/Scope Perry Preschool Study see Schweinhart et al. [1993] and on the Abecedarian Project, see Campbell et al. [1998].

More recently PSID Child Supplement began to collect data on a nationally representative sample of children. This dataset will enable one to link a child's school success and the labor market outcomes to a child's preschool experiences regarding the child rearing methods, home environment, teaching methods followed in schools. While the dataset contains the school performance of these children, the sampled cohorts will have data on labor market outcomes available only many years later in the future.

7.2 Production of non-cognitive skills

We show in the next two subsections that non-cognitive skills are important determinants of earnings and learning. In this section we consider the production process of these skills.

The literature in sociology, psychology, early childhood development and physiology suggest that early childhood investment is the most crucial input for development of cognitive and non-cognitive skills. The studies in these literatures link school success to home environment, child rearing practices, neighborhood type in which the kid is raised. For instance, the Coleman report [1966] and many subsequent studies find that family capital, which captures family tradition and values towards economic success and education, and social capital, which captures the benefits of social bonds, social norms, social networks, the social bonds between adults and children and among children in a neighborhood are of immense value during a child's growing up. These factors affect parental choices of preschool investment and child rearing methods which in turn determine a child's cognitive and non-cognitive abilities that affect their learning and earning. Physiology literature produces ample evidence that the human brain develops extremely rapidly during age [2-4], and the type of stimulations regarding health and learning that the child experience during this period is a critical determinant of a child's cognitive, social and motor developments. Child psychology literature also points out that a structured preschool stimulation also boosts a child's self-confidence, school preparedness, parents' and teachers' assessment of the child's ability. These in turn create a conducive learning environment for the child over many more years of schooling, beginning with the elementary school. See Entwisle [1995], and Barnett [1995] for more on these issues.

We construct the variables of our study as follows:

Early childhood inputs and home environment: We take father's and mother's education levels to measure family background. The NLSY dataset has poor measures of respondent's early childhood inputs. It has only a binary variable containing information on whether the respondent had preschool (does not include Head Start) experience or not. We treated individuals with Head Start experience as no preschool. Notice that this will lead to underestimation of the effect of preschool investment. We use the revised AFQT score to measure innate ability.

Socialization skill (σ): Each respondent were asked how social towards others he/she felt at age 6, expressed in the scale of 1 to 4, the highest number represents most social. We create a binary sociability variable by assigning the value 1 if a respondent reported a value of 3 or 4 and assigning 0 otherwise.

Motivational skill (μ): The educational goal (μ) is the grade that the respondent in 1979 expected to achieve.

Rosenberg measure of self-esteem skill (η): It measures the positiveness with which individuals regard themselves, i.e., a positive sense of self. Six questions were taken from the classic Rosenberg (1965) scale in the NLSY surveys. There is, however, no well accepted definition of adequate self-esteem. Based on the distribution, we divided the 25-point scale by treating a score of 20 or greater indicated a high self-esteem and assign a value 1 to η and a value 0 to η otherwise.

Pearlin mastery scale of internal self-concept (ϕ): This measures to what extent individuals believe that their life chances are under their control (Pearlin et al. 1981). This is similar to Rotter scale of self-control. The respondents were asked seven questions yielding scores ranging from 0 to 28. We assign the value 1 representing a high sense of self-control to respondents with a score between 23 and 28 inclusive, otherwise we assign a a value 0.

We estimated Logit models for the cognitive and non-cognitive skills for the child sample. These parameter estimates are then used to fix the transition probability $p\left(x'|x,a\right)$. We report in table 1 the parameter estimates for specifications in which only the significant regressors (x and a). In our structural maximum likelihood estimations, however, we have reported sensitivity of parameter estimates for this specification and speciations in which we have used both significant and insignificant parameter estimates for $p\left(x'|x,a\right)$.

From table 1, it is clear that after controlling for parents' grade, preschool experience has significantly positive effect on the socialization skill, the motivational skill and on the levels of talent and schooling but has no effect on Pearlin measure of internal self-cocept and the Rosenberg measure of self-esteem. The estimates in the table also show that level of talent has strong positive effect on all skills.

It will be interesting to see if preschool has stronger positive effect on socialization and motivational skills of children of poorer SES. If so, then the preschool could be a used to compensate for the better HOME environment that the well to do counterpart of these children have, and through preschool we can achieve a higher equality of opportunities by equalizing the differences in cognitive and non-cognititve skills of the children.

Table 1: Logit model of cognitive and non-cognitive skills.

	Talent τ	Socialization σ	Motivation μ	Self-concept (Pearlin): ϕ	Self-Esteem (Rosenberg):η	College* s
Intercept	-3.587 (3.46)	1.164 (11.60)	0.428 (0.92)	-1.106 (13.56)	0.672 (8.96)	-4.694 (18.22)
Own Talent		0.835 (5.55)	1.036 (7.60)	0.402 (4.62)	0.596 (5.28)	1.877 (12.08)
Parent's Talent	1.707 (15.91)					
σ :Socialisation				0.243 (3.09)		0.477 (3.28)
μ : Motivation (Education Goal)						2.726 (17.28)
ϕ : Internal Self-Concept (Pearlin)			0.503 (2.78)			0.443 (2.26)
η : Self-Esteem (Rosenberg)		0.372 (3.45)	0.325 (3.35)	0.380 (4.26)	0.551 (6.08)	1.245 (4.94)
Parents' Grade	1.814 (1.75)					1.339 (5.17)
Preschool	0.424 (4.47)	0.310 (3.03)	0.190 (2.09)			0.668 (3.72)

Note: *While for other models the attributes Socilazation, Motivation, Internal Self-concept (Pearlin) and Self-esteem (Rosenberg) in the first column are parents' attributes, for this model, these attributes in column one are the individual's own attributes, and this model is estimated using the 1979 youth sample.

7.3 An Augmented Earnings Function - Role of cognitive and non-cognitive skills

In this section we examine the effect on earnings of non-cognitive skills such as social, motivational, self-esteem and internal self-concept skills together with the effect of the cognitive skills such as innate ability and grades. The previous studies included only innate ability, schooling level and school quality as the main determinants of earnings. While preschool investment is an important determinant of these skills, we also included preschool binary variable as one of the regressors in the earnings function to see if it has an independent effect. In our specification, we included two dummy variables, High School (taking value 1 if a respondent had the high school degree) and College (if a respondent graduated from college). These dummy variables together with grade variable are to capture the earnings premiums for graduating from high school and college. Since we included AFQT score which is a reasonably good measure of one's innate ability, we do not have the ability biases in our estimates. We use the yearly earnings data to estimate the model.

Table 1 shows the parameter estimates of this augmented earnings function. The first column is for all three races together and the next three columns give the estimates for the Hispanics, Blacks and the Whites ethnic groups separately. It is clear from the estimates that after controlling for innate ability, family background and the schooling level, all four measures of non-cognititve skills have significant positive effect on earnings for all ethnic groups. Preschool has independent positive effect only for blacks. It is also interesting to note that a college graduate earns 8.35% higher returns in the overall population, and for Blacks and Hispanics this premium is even higher, slightly above 10%. The sociability skills are significant only for White but not for Black and Hispanic workers.

7.4 Estimation of Schooling Function

We consider two specifications of the schooling function $s^* (\tau', \sigma', \mu', \eta', \phi', a, \varepsilon')$. In the first specification, we assume that the schooling level is a continuous variable. We specify the optimal reaction function $s^* (\tau', \sigma', \mu', \eta', \phi', a, \varepsilon')$ as a linear function. We assume that the vector of random variable ε' constitutes the error term of the linear model and satisfies all the assumptions of the OLS model.[2] We included the cognitive and non-cognitive skills together with the family background variable as measured by the parent's education level. The parameter estimates from this model are shown in table 3 for all ethnic groups together,

[2]More generally we could assume that $E\left(\varepsilon_s' | \tau', \sigma', \mu', h\right) = 0$ and use GLS method to correct for heteroskedasticity.

Table 2: Determinants of earnings -- role of cognitive and non-cognitive skills (from the parent sample)

Variables	All Races	Hispanic	Black	White
Intercept	2.369 (31.28)	2.355 (13.64)	0.813 (4.44)	2.613 (27.27)
Own Talent	0.005 (32.28)	0.004 (8.79)	0.006 (12.07)	0.003 (15.67)
Grade	0.054 (22.82)	0.037 (7.83)	0.088 (14.08)	0.057 (18.43)
Dummy for High School	0.065 (8.22)	0.048 (2.82)	0.028 (1.52)	0.095 (9.07)
Dummy for College	0.088 (7.61)	0.097 (2.83)	0.109 (3.59)	0.084 (6.30)
Age	0.319 (70.49)	0.306 (29.04)	0.354 (32.92)	0.314 (56.03)
Square of Age	-0.004 (51.59)	-0.004 (20.84)	-0.004 (24.53)	-0.004 (40.96)
Mother's grade	0.000 (0.30)	0.011 (4.29)	0.016 (4.35)	-0.003 (1.12)
Father's grade	0.007 (5.74)	0.004 (1.77)	-0.006 (2.29)	0.012 (6.93)
Dummy for preschool	0.001 (0.15)	-0.048 (2.32)	0.060 (3.10)	0.007 (0.63)
Socialization	0.013 (1.90)	-0.026 (1.58)	0.025 (1.46)	0.014 (1.65)
Motivation (education goal)	0.002 (1.16)	0.016 (3.52)	0.007 (1.37)	0.007 (2.72)
Self-esteem(Rosenberg)	0.018 (16.32)	0.026 (9.51)	0.018 (6.49)	0.018 (13.50)
Internal self-control(Pearlin)	0.024 (21.07)	0.032 (11.49)	0.026 (9.36)	0.019 (13.46)
Gender	-0.512 (74.98)	-0.491 (30.43)	-0.365 (21.98)	-0.578 (68.77)
R^2	0.381	0.396	0.375	0.383
n	81,005	13,769	15,972	51,264

Notes: Absolute t-values are in parentheses.

and also separately for the Hispanic, Black and White populations. It is clear from the estimates that the main determinant of grade is the innate ability measured by AFQT score. After controlling for family background, we find that the sociability skill has no effect on the schooling level.

In our second specification, we consider only two levels of schooling: college and more ($s = 1$), and no college ($s = 0$). Again we assume that $s^* (\tau', \sigma', \mu', \eta', \phi', a, \varepsilon')$ is represented by a Probit model. We use a subset of the above regressors in this specification and use these estimates to calibrate our basic model in Eq. 2. The college status of parents is defined by assigning the value 1 if at least one parent had some college, and 0 otherwise. The parameter estimates from this model are shown in table 1 for all ethnic groups together. It is clear from the estimates that the main determinant of grade is again the innate ability measured by AFQT score. After controlling for family background, we find that all cognitive and non-cognitive skills are significant determinants of the schooling level, the measure of motivational skills has the most significant positive effect on the probability of completing college.

7.5 Optimal Parental Preschool Investment Decision

We assume that the state variables $s, \tau, \sigma, \mu, \eta$ and ϕ are all binary, all components of the random vector ε is continuous which are observed by the decision maker but not by the econometrician, and the preschool investment decision a is also a binary variable, taking value 1 when parents decide to invest in preschool and 0 otherwise. For most children, we have two parents but in our model we have assumed one parent. We could take mother as the parent. We have instead used both parent's information as follows: We construct parent's binary schooling variable s by assigning $s = 1$ if the average grades of two parents is more than 12, otherwise $s = 0$. We assume that τ is biologically inherited and it is not influenced by preschool investment. We create the binary variable τ assigning value 1, i.e., an individual is highly talented if the AFQT score of the individual is 70 or higher, and assigning value 0 otherwise.

The estimate of the preschool investment cost depends on the calibrated value of the altruism parameter β as can be seen from table 5. Schweinhart et al. took average yearly preschool cost to be \$6178 per year. Consistent with their study, we calibrate the altruism parameter to $\beta = 0.35$ for our analysis to be consistent with their cost estimate. The optimal preschool investment decision and the value function are shown respectively in columns 3 and 4 of table 6.

Table 3: Determinants of grade -- role of cognitive and non-cognitive skills (from the parent sample)

Variables	All Races	Hispanic	Black	White
Intercept	2.753 (13.24)	3.324 (5.95)	3.245 (7.66)	2.335 (8.53)
Own Talent	0.028 (29.55)	0.035 (11.38)	0.030 (12.85)	0.028 (22.19)
Mother's grade	0.059 (6.48)	0.027 (1.41)	0.113 (6.03)	0.076 (5.43)
Father's grade	0.028 (3.77)	-0.002 (0.12)	0.004 (0.28)	0.067 (6.44)
Dummy for Preschool	0.266 (4.85)	-0.086 (0.57)	0.227 (2.25)	0.301 (4.25)
σ : Socialization	0.037 (0.83)	-0.128 (1.04)	0.119 (1.34)	0.051 (0.94)
μ : Motivation (Education Goal)	0.458 (40.75)	0.425 (13.93)	0.348 (14.98)	0.468 (31.43)
η : Self-Esteem (Rosenberg)	0.035 (5.10)	0.042 (2.10)	0.069 (4.83)	0.020 (2.32)
η : Internal self-control(Pearlin)	0.034 (4.78)	0.055 (2.75)	0.010 (0.73)	0.034 (3.87)
Gender	0.182 (4.27)	0.126 (1.06)	0.464 (5.47)	0.117 (2.24)
R^2	0.560	0.488	0.541	0.585
n	5,782	1,012	1,218	3,552

We consider a public policy of providing preschool to children of poor socioeconomic status (SES) in all periods. We define a parent to fall in the poor SES if his earnings is less than *70* percent of the average earnings in economy. This will incur a per capita cost, but such policy may also improve social mobility, earnings inequality and lead to a higher level of per capita long-run earnings. We examine if the gain from per capita earnings can outpace the cost of providing such a social insurance program. We also look at its within generation effects on earnings, and on intergenerational social and college mobility.

Table 4: Maximum likelihood parameter estimates given two different estimates of $p(x'|x,a)$ and altruism parameter $\beta = 0.35$.

	Parameter Estimates given $p(x'|x,a)$ using	
	only significant $x's$	all $x's$
Marginal utility $(\hat{\theta}_0)$ from average earnings	6.729 (5.136)	8.452 (5.646)
Utility cost $(\hat{\theta}_1)$ of Preschool investment	4.636 (9.391)	4.761 (10.077)
Annualized cost in dollars $1000 \times (\hat{\theta}_1/\hat{\theta}_0)$	689.032	563.229
Percent of poor SES population	28.39	36.30
Per capita cost to society ('000 dollars)	0.196	0.204
Per capita change in earnings ('000 dollars)	0.310	0.432
Log-likelihood	-1039.626	-1037.236

Note: Absolute value of t-statistics are in parentheses.

8 Economic Benefits from Public Provision of Preschool

We have shown that investment in preschool enhances certain skills that are important for learning and earning. We have also seen that the parents of poor SES do not invest in their children's preschool. If preschool is publicly provided for the children of poor SES, it will have many economic benefits: It will increase social mobility, it will reduce income inequality, it will improve college enrollment rate, it will improve the community or criminal behavior, and it will also bring higher tax revenues because more workers will be earning higher wages. It is important to note that the magnitude of the effect of publicly provided

Table 5: Sensitivity of maximum likelihood estimates with variations of the altruistic parameter β.

β	$\hat{\theta}_0$	t-stat of $\hat{\theta}_0$	$\hat{\theta}_1$	t-stat of $\hat{\theta}_1$	annualized per capita costs and benefits in $ '000: costs: parent	costs: tax payer	benefits: $\triangle\bar{w}$
0.030	82.313	4.484	4.430	8.572	0.054	0.015	0.313
0.070	35.151	4.566	4.458	8.673	0.127	0.036	0.313
0.110	22.274	4.647	4.485	8.775	0.201	0.057	0.313
0.150	16.255	4.729	4.512	8.877	0.278	0.079	0.312
0.190	12.761	4.810	4.538	8.979	0.356	0.101	0.312
0.230	10.476	4.892	4.563	9.082	0.436	0.124	0.311
0.270	8.863	4.973	4.588	9.185	0.518	0.147	0.311
0.310	7.661	5.055	4.613	9.288	0.602	0.171	0.310
0.350*	6.729	5.136	4.637	9.391	0.689	0.196	0.310
0.390	5.985	5.218	4.660	9.495	0.779	0.221	0.309
0.430	5.376	5.299	4.682	9.599	0.871	0.247	0.308
0.470	4.867	5.380	4.704	9.704	0.967	0.274	0.308
0.510	4.435	5.462	4.726	9.809	1.065	0.302	0.307
0.550	4.064	5.543	4.746	9.914	1.168	0.332	0.306
0.590	3.741	5.624	4.766	10.020	1.274	0.362	0.306
0.630	3.456	5.705	4.786	10.126	1.385	0.393	0.305
0.670	3.204	5.787	4.804	10.233	1.500	0.426	0.304
0.710	2.978	5.868	4.822	10.340	1.619	0.460	0.303
0.750	2.774	5.949	4.839	10.448	1.744	0.495	0.302
0.790	2.590	6.030	4.856	10.556	1.875	0.532	0.301
0.830	2.421	6.111	4.872	10.664	2.012	0.571	0.300
0.870	2.267	6.192	4.887	10.774	2.156	0.612	0.299
0.910	2.125	6.273	4.901	10.883	2.306	0.655	0.298
0.950	1.994	6.354	4.915	10.994	2.465	0.700	0.297
0.990	1.872	6.435	4.928	11.105	2.633	0.747	0.296

Table 6: Equilibrium Solution

$[\tau, \sigma, \mu, \eta, \phi, s]$	p_0	Earnings	$P_b(a=1\|x)$	$P_a(a=1\|x)$	$optV_b$	$optV_a$	p_b^*	p_a^*
[0, 0, 0, 0, 0, 0]	0.1797	4.1520	0.0735	1.0000	60.1545	62.5914	0.0088	0.0075
[0, 1, 0, 0, 0, 0]	0.0013	4.3993	0.0740	1.0000	62.1775	64.6075	0.0351	0.0334
[0, 0, 1, 0, 0, 0]	0.0029	4.7769	0.0735	1.0000	64.3592	66.7961	0.0155	0.0136
[0, 1, 1, 0, 0, 0]	0.0000	5.0241	0.0740	1.0000	66.3822	68.8122	0.0571	0.0544
[0, 0, 0, 0, 1, 0]	0.0029	6.2648	0.0843	1.0000	76.4401	78.9237	0.0226	0.0195
[0, 1, 0, 0, 1, 0]	0.0000	6.5120	0.0848	1.0000	78.5247	80.9992	0.0920	0.0866
[1, 0, 0, 0, 0, 0]	0.0665	6.7053	0.1312	1.0000	79.0355	82.0031	0.0001	0.0001
[0, 0, 0, 1, 0, 0]	0.3029	6.8013	0.0822	1.0000	78.6578	81.1644	0.0043	0.0038
[0, 0, 1, 0, 1, 0]	0.0000	6.8896	0.0843	1.0000	80.6448	83.1284	0.0297	0.0246
[1, 1, 0, 0, 0, 0]	0.0006	6.9525	0.1320	1.0000	81.0655	84.0271	0.0009	0.0010
[0, 1, 0, 1, 0, 0]	0.0060	7.0485	0.0827	1.0000	80.6867	83.1864	0.0178	0.0170
[0, 1, 1, 0, 1, 0]	0.0000	7.1369	0.0848	0.0812	82.7293	83.0784	0.1014	0.0897
[1, 0, 1, 0, 0, 0]	0.0019	7.3301	0.1312	0.1235	83.2402	83.6627	0.0002	0.0002
[0, 0, 1, 1, 0, 0]	0.0342	7.4261	0.0822	0.0778	82.8625	83.2858	0.0071	0.0062
[1, 1, 1, 0, 0, 0]	0.0000	7.5774	0.1320	0.1246	85.2701	85.6776	0.0015	0.0015
[0, 1, 1, 1, 0, 0]	0.0013	7.6734	0.0827	0.0785	84.8914	85.2989	0.0261	0.0244
[1, 0, 0, 0, 1, 0]	0.0010	8.8180	0.1416	0.1348	95.3049	95.6369	0.0004	0.0004
[0, 0, 0, 1, 1, 0]	0.0215	8.9140	0.0910	0.0871	94.9085	95.2359	0.0115	0.0100
[1, 1, 0, 0, 1, 0]	0.0000	9.0653	0.1420	0.1357	97.3925	97.7091	0.0030	0.0033
[0, 1, 0, 1, 1, 0]	0.0003	9.1613	0.0913	0.0877	96.9992	97.3112	0.0470	0.0441
[1, 0, 0, 1, 0, 0]	0.1705	9.3545	0.1409	0.1330	97.5396	97.9225	0.0001	0.0001
[1, 0, 1, 0, 1, 0]	0.0010	9.4429	0.1416	0.1348	99.5096	99.8416	0.0004	0.0004
[0, 0, 0, 0, 0, 1]	0.0092	9.4477	0.1346	0.1259	100.6712	101.0250	0.0002	0.0002
[0, 0, 1, 1, 1, 0]	0.0048	9.5389	0.0910	0.0871	99.1132	99.4406	0.0128	0.0105
[1, 1, 0, 1, 0, 0]	0.0063	9.6018	0.1416	0.1340	99.5746	99.9434	0.0006	0.0007
[1, 1, 1, 0, 1, 0]	0.0000	9.6901	0.1420	0.1357	101.5972	101.9138	0.0027	0.0028
[0, 1, 0, 0, 0, 1]	0.0000	9.6949	0.1344	0.1260	102.7032	103.0454	0.0011	0.0013
[0, 1, 1, 1, 1, 0]	0.0000	9.7862	0.0913	0.0877	101.2039	101.5158	0.0428	0.0373
[1, 0, 1, 1, 0, 0]	0.0285	9.9794	0.1409	0.1330	101.7442	102.1272	0.0001	0.0001
[0, 0, 1, 0, 0, 1]	0.0006	10.0725	0.1346	0.1259	104.8759	105.2297	0.0042	0.0047
[1, 1, 1, 1, 0, 0]	0.0006	10.2266	0.1416	0.1340	103.7792	104.1481	0.0008	0.0009
[0, 1, 1, 0, 0, 1]	0.0000	10.3198	0.1344	0.1260	106.9078	107.2501	0.0250	0.0293
[1, 0, 0, 1, 1, 0]	0.0146	11.4673	0.1474	0.1409	113.7605	114.0576	0.0002	0.0003
[0, 0, 0, 0, 1, 1]	0.0013	11.5604	0.1193	0.1131	117.1245	117.4035	0.0015	0.0016
[1, 1, 0, 1, 1, 0]	0.0000	11.7145	0.1476	0.1415	115.8532	116.1366	0.0020	0.0021
[0, 1, 0, 0, 1, 1]	0.0000	11.8077	0.1185	0.1127	119.2084	119.4756	0.0101	0.0116
[1, 0, 0, 0, 0, 1]	0.0006	12.0009	0.1672	0.1580	122.9650	123.2108	0.0000	0.0000
[1, 0, 1, 1, 1, 0]	0.0054	12.0921	0.1474	0.1409	117.9652	118.2623	0.0002	0.0002
[0, 0, 0, 1, 0, 1]	0.0409	12.0969	0.1260	0.1183	119.4114	119.7248	0.0001	0.0001

Table 7: Continuation of Table 6.

$[\tau, \sigma, \mu, \eta, \phi, s]$	p_0	Earnings	$P_b(a=1\|x)$	$P_a(a=1\|x)$	$optV_b$	$optV_a$	p_b^*	p_a^*
[0, 0, 1, 0, 1, 1]	0.0000	12.1853	0.1193	0.1131	121.3292	121.6082	0.0257	0.0272
[1, 1, 0, 0, 0, 1]	0.0000	12.2482	0.1666	0.1578	125.0072	125.2455	0.0003	0.0004
[1, 1, 1, 1, 1, 0]	0.0000	12.3394	0.1476	0.1415	120.0579	120.3413	0.0015	0.0015
[0, 1, 0, 1, 0, 1]	0.0010	12.3442	0.1254	0.1181	121.4449	121.7480	0.0009	0.0010
[0, 1, 1, 0, 1, 1]	0.0000	12.4325	0.1185	0.1127	123.4131	123.6803	0.1394	0.1546
[1, 0, 1, 0, 0, 1]	0.0000	12.6258	0.1672	0.1580	127.1697	127.4155	0.0006	0.0007
[0, 0, 1, 1, 0, 1]	0.0076	12.7218	0.1260	0.1183	123.6161	123.9295	0.0030	0.0033
[1, 1, 1, 0, 0, 1]	0.0000	12.8730	0.1666	0.1578	129.2119	129.4501	0.0068	0.0077
[0, 1, 1, 1, 0, 1]	0.0006	12.9690	0.1254	0.1181	125.6496	125.9527	0.0175	0.0200
[1, 0, 0, 0, 1, 1]	0.0006	14.1137	0.1384	0.1324	139.1534	139.3505	0.0003	0.0003
[0, 0, 0, 1, 1, 1]	0.0257	14.2097	0.1081	0.1030	135.7709	136.0161	0.0012	0.0013
[1, 1, 0, 0, 1, 1]	0.0000	14.3609	0.1373	0.1316	141.2364	141.4260	0.0035	0.0039
[0, 1, 0, 1, 1, 1]	0.0010	14.4569	0.1071	0.1024	137.8560	138.0911	0.0080	0.0091
[1, 0, 0, 1, 0, 1]	0.0165	14.6502	0.1465	0.1391	141.5275	141.7475	0.0000	0.0000
[1, 0, 1, 0, 1, 1]	0.0003	14.7385	0.1384	0.1324	143.3581	143.5551	0.0039	0.0043
[0, 0, 1, 1, 1, 1]	0.0032	14.8345	0.1081	0.1030	139.9756	140.2208	0.0169	0.0176
[1, 1, 0, 1, 0, 1]	0.0013	14.8974	0.1458	0.1387	143.5690	143.7823	0.0003	0.0004
[1, 1, 1, 0, 1, 1]	0.0000	14.9858	0.1373	0.1316	145.4411	145.6307	0.0426	0.0476
[0, 1, 1, 1, 1, 1]	0.0006	15.0818	0.1071	0.1024	142.0606	142.2957	0.0898	0.0972
[1, 0, 1, 1, 0, 1]	0.0029	15.2750	0.1465	0.1391	145.7322	145.9522	0.0005	0.0006
[1, 1, 1, 1, 0, 1]	0.0003	15.5223	0.1458	0.1387	147.7737	147.9870	0.0059	0.0067
[1, 0, 0, 1, 1, 1]	0.0247	16.7629	0.1203	0.1157	157.6138	157.7899	0.0003	0.0003
[1, 1, 0, 1, 1, 1]	0.0013	17.0102	0.1191	0.1148	159.6961	159.8658	0.0034	0.0039
[1, 0, 1, 1, 1, 1]	0.0054	17.3878	0.1203	0.1157	161.8185	161.9945	0.0034	0.0037
[1, 1, 1, 1, 1, 1]	0.0000	17.6350	0.1191	0.1148	163.9008	164.0705	0.0369	0.0410

preschool will depend on if the social protection will be available to all future generations or it is just a one time policy.

While looking at the magnitude of the estimated economic benefits below, it is important to keep in mind that the effects that we report are underestimated for many reasons: First, we have treated the Head Start children same as children without preschool. Second, the preschool programs that the respondents attended were the ones that existed during the sixties. The quality of preschool programs ever since has improved significantly and thus the effects of current preschool programs will be much higher than the estimates that we have. Third, we have calibrated our model cost to a higher cost of a high quality pilot porgram.

Note that since ε does not affect earnings, the optimal a depends only on the observable component x of a parent's state variable, i.e. optimal preschool plan is $a(x)$. In the absence of the social contract, suppose the parents follow the optimum preschool investment plans $a(x)$ as shown in table 6. The invariant distribution of the corresponding transition matrix $\{p(x'|x, a(x)), x \in X\}$ is shown in table 6 under the heading $P_b(a=1|x)$. The interpretation of this invariant distribution is as follows: If $P_b(a=1|x)$ is the distribution of population over the observable states of generation t, and the parents of generation t follow the optimal preschool investment plan $a(x)$, the distribution of population of the next generation will also be $P_b(a=1|x)$.

8.1 Social Mobility

A number of mobility measures for a transition matrix appear in the literature. Sommers and Conlisk [1979] argued that out of the existing measures, $1-\lambda_{\max}$ is the most appropriate measure of social mobility, where $\lambda_{\max}$ is the second highest positive eigenvalue of the transition matrix (the highest positive eigenvalue of a transition matrix is always 1). We use this measure of social mobility to examine how the introduction of the social contract would improve social mobility. Our estimate of the measure of social mobility before the introduction of the social contract is 0.568759 and after the introduction of the social contract program, it improves to 0.598074. The estimate of 0.568759 for the measure is very close to the estimates found in other studies of social mobility in the US.

8.2 College Mobility

Denote by $Q^s = [q_{ij}], i, j = 1, 2$, the intergenerational college mobility matrix in which state 1 represents no college and state 2 represents college and higher. The element q_{ij} represents the probability that a child of a parent of college education status i will move to the college education status j, for all i and $j = 1, 2$. We report below the estimated college mobility matrices, the corresponding invariant distributions, and the estimates of the mobility measure before and after the introduction of the social contract. These estimates indicate that the introduction of the social contract will increase college enrollment from a 32.90 percent to a 37.21 percent, i.e. a 4.31 percent increase for a child of non-college parent. And the percentage of college enrolled population will increase in the long-run from the rate of 48.17 percent without social contract to a higher rate of 51.18 percent with the social contract. That is, there will be about a 3.01% increase in college enrollments in the long-run.

College mobility statistics before introduction of social contract:

$$Q_b^s = \begin{bmatrix} 0.6710 & 0.3290 \\ 0.3541 & 0.6459 \end{bmatrix}, p_b^s = \begin{bmatrix} 0.518327 & 0.481673 \end{bmatrix}, 1 - \lambda_{\max,b}^s = 0.683070$$

College mobility statistics after introduction of social contract:

$$Q_a^s = \begin{bmatrix} 0.6279 & 0.3721 \\ 0.3550 & 0.6450 \end{bmatrix}, p_a^s = \begin{bmatrix} 0.488177 & 0.511823 \end{bmatrix}, 1 - \lambda_{\max,a}^s = 0.727102$$

8.3 Income Inequality

Preschool experience will increase the incomes of the children of poor SES and thus it will reduce the income gap between the rich and the poor. Using the Gini-coefficient to measure income inequality, we would expect that over time the income inequality will improve. In the long-run, the income distribution that one observes is the invariant distribution. Thus we compute the Gini-coefficient of income inequality for the invariant income distribution before the introduction of the social contract and compare it with the Gini-coefficient for the invariant income distribution after the introduction of the social contract. The estimated Gini-coefficients are respectively 0.2133 without the social contract, and 0.2087 with the social contract. The estimated Gini-coefficient of earnings 0.2133 turns out to be very close to the estimates found in other studies on US. We note that the social contract of publicly providing preschool to children of poor SES leads to a significant reduction in the inequality of the long-term earnings.

8.4 Tax Burden of the Social Contract

Suppose the government provides preschool to the children of poor SES perpetually. We know that the size of the population of poor SES will become smaller over time. Thus the resource needs of the program will become smaller, and the tax revenues will become higher over time. We can look at the stream of these costs and benefits to the society and then compute the average per period costs and benefits to calculate the tax-burdens of the social contract. Applying the Ergodic theorem, however, this boils down to computing the costs and benefits of the invariant distribution that will result after the introduction of the social contract.

Approximately 28.39 percent of the population will fall in the poor socioeconomic status using our definition. Thus the per capita cost of the social contract to the economy in the long-run is \$195.638 but the gain in per capita income due to the introduction of the social contract is \$309.60, so there is a net gain to the economy. This net gain is based on a reasonable value of the altruistic parameter β. The simulation results in our sensitivity analysis shows that, the lower is the value of the altruism parameter β, the higher is the gain from the introduction of the social contract. The economic reason for this is quite obvious. When parents have lower altruism towards children, they will invest less on their children's preschool since such investment decreases their own felicity index and increase welfare of the children which got a lower weight when β has lower value. This estimate of net gain is based on calibrating the value of β to the cost data of a high cost program as noted earlier whose benefits are supposed to be higher than our estimated benefits. Thus, this gain is an underestimate of the actual net benefit. Furthermore, our benefit calculation does not take into account other public savings such as savings from welfare assistance programs and savings to the criminal justice system and potential victims of crimes. If we incorporate these, the returns will be much higher. Using data from the High/Scope Perry Preschool Program, Schweinhart et al. estimated a total benefit of \$7.16 from all these sources for each dollar spent on the preschool program.

9 Conclusion

This paper formulated an altruistic model of parental preschool investment within a structural dynamic programming framework. The paper provided conditions for the local and global identification of the non-parameteric and parametric structural parameters of the dynamic programming model. It used the NLSY79 and NLSY79 Children and Young Adult datasets for all emprical estimations of the model.

The paper estimated the production processes of two types of cognitive skills - the IQ score and the schooling level, and four types of non-cognitive skills - the socialization skill, the motivational skill, the Rosenberg measure of self-esteem skill and the Pearlin mastery scale of internal self-concept skill. The paper found that the preschool boosted significantly all the cognitive and non-cognitive skills, but not the Rosenberg measure of self-esteem skill and the Pearlin measure of internal self-concept skill. Moreover, all these cognitive and non-cognitive skills have significant positive effects on the level of schooling and the labor market earnings of individuals.

The paper estimated the structural parameters and then used those to carry out a Lucas-Critique free policy analysis to examine the effect of publicly providing preschool to economically disadvantged children. Taking into account the within generation and between intergenerations effects of such a policy, the paper estimates that in the long run the preschool social contract policy

- improves the social mobility from 0.569 to 0.598, measured in a scale of 0 to 1 .
- improves the college mobility from 0.683 to 0.727, measured in a scale of 0 to 1 and increases the college completion rate of the children of non-college educated parents from 32.9 percent to 37.21 percent, i.e., a 4.31 percent increase.
- reduces the earnings inequality measured by the Gini coefficient in a scale of 0 to 1 from 0.213 to 0.209.

The paper estimates that the preschool social contract policy costs the economy $195.64 per capita but increases the per capita earnings by $309.60. That is, there is a significant net positive gain to the tax payers from the introduction of the preschool social contract program.

The positive effects of the preschool social contract will be even higher in reality because we have used the estimated cost of a high cost, high quality pilot preschool program, but used the estimated benefits from the lower cost, lower quality preschool programs that existed in the 1970s.

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