The Black-White Income Mobility Gap and Investment in Children's Human Capital

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Abstract

At every percentile of the last generation's earnings distribution black sons experience a lower probability of upward mobility with respect to their fathers position than their white counterparts. Furthermore, the intergenerational elasticity of earnings is significantly lower for blacks than it is for whites. This paper goes beyond a comparison of aggregate measures of parental income to analyze the intergenerational transmission of earnings by building a dynamic model of parental investments in children's human capital. Parents can make investments in their child's human capital throughout the childhood period, during which each year's investment boosts their child's earnings potential and the productivity of future human capital investments. Parents' ability to invest in their child is determined by their earnings when the child is growing up. Earnings shocks and parental separation negatively affect the accumulation of children's human capital. The model also permits differences in preferences and in the technology of human capital production and it allows for the possibility of statistical discrimination. The paper assesses the relative contributions of all these factors in explaining the differences in earnings mobility. The model is estimated using data from the Panel Study of Income Dynamics which includes observations on parental life cycles as well as children's adult outcomes. Results show that the variation of parental income during childhood, caused by the instability of families and transitory income shocks can generate the observed mobility gap.

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1 Introduction

It is well known that positions in the distribution of earnings are not independent across generations. Children of rich parents generally remain at the top of the earnings distribution, while children with parents located at the bottom rarely reach the upper percentiles[1]. Estimates of the intergenerational elasticity of income, the most common measure of intergenerational mobility in the empirical literature, also know as the IGE (see for example **????**), indicate that it would take about 3-6 generations for dynasties to reach the national average if they started out at half the mean income in the US.[2] Given these facts on the intergenerational persistence of economic status, African Americans are clearly disadvantaged due to centuries of discrimination, and one would hope, that they have slowly started to catch up in the last decades following the civil rights movement. Unfortunately there is evidence to the contrary.

Sons of black parents have a higher probability of falling below their father's percentile in the earnings distribution than white sons at *every* percentile of the father's distribution. **?** and **?** estimate measures of upward mobility using the NLSY79 cohort of black and white men. They find that black sons experience a lower probability of upward earnings mobility with respect to their parent's position in the family income distribution. **?** reports evidence from PSID data indicating that black families are more likely than white families to remain in the bottom quintile of the family income distribution in the next generation and less likely than whites to remain in the top quintile across generations. I confirm these facts for black and white fathers and sons using data on earnings from the PSID and earnings distribution boundaries from the Census (section **??**).

Furthermore, the IGE is significantly lower for black father-son pairs than for white fathers and sons. The estimated IGE of earnings for white fathers and sons in my sample is around 0.35, while it is approximately 0.2 for blacks. **?** also finds lower intergenerational correlations in family income for black families. This lower dependence of blacks' economic status on their fathers' is not an indication of higher overall mobility, since blacks are more likely to move down (less likely to move up) at every percentile of the income distribution. Instead, it seems there are crucial differences in

[1]See for example **?** which gives a comparison of intergenerational mobility in Europe and the USA.

[2]The IGE is the coefficient on fathers' income in a log-linear regression of sons' income on fathers'. Typical estimates of the IGE for the U.S. range from 0.3 to 0.6, depending on the sample and income measures used. See (**?**) for a summary table with estimates obtained in the literature.

the transmission of income across generations that cause black men to move down in the overall earnings distribution relative to white men.

I examine potential explanations for this black-white mobility gap in a structural model of parental lifecycle investments in children's human capital. The model focuses on the role of parental investments in human capital during *childhood* in generating intergenerational transmission of economic status. This is motivated by recent work on the importance of early childhood investments (see **???**). In a collection of papers on the technology of skill formation James Heckman and his co-authors investigate the malleability of cognitive and non-cognitive skills over the childhood period. One of their main findings is that investments at different stages during childhood are complements. Thus early investments in skills need to be followed up with later investments in order for the effects not to diminish as the child grows up, while late investments are less productive, if children had suffered disadvantages in early skill formation.

Human capital accumulated during childhood is important for adult outcomes. The heterogeneity in skills of teenagers has been found to play a major role in explaining subsequent secondary schooling and labor market outcomes. **??** find significant effects of the "initial endowment" of skills at age 16 in explaining differing career paths between individuals, while **?** establish that the black-white earnings gap is largely due to "pre-market" factors (measured at age 16).

Since parents cannot borrow against the future income of their child, they are credit constrained in their investment decision during the most critical years for children's skill formation.[3] Thus, if parental income plays a direct role in the transmission of labor market success between the generations, it must do so during the childhood. The intergenerational mobility literature, to the best of my knowledge, has not considered the evolution of parental income during the childhood period in explaining intergenerational income mobility.

My model takes note of the findings on children's skill formation by assuming a human capital production function in which parental investments at every age of the child, starting at birth until age 15, are complementary. At age 16 the child makes his own schooling and career decisions given his human capital. Parents anticipate the child's decision and make optimal investments at the

[3]There's a large literature on credit constraints during college, which shows that they cannot explain differences in college attainment (**?????**). But also see **?**, who demonstrate that parental income might have become more important recently due to rising tuition costs.

earlier ages, maximizing their utility from household consumption and expected utility from their child's future earnings. Parents' investment potential is determined by their income realization, which is a function of the parents' marital status and transitory wage shocks. The marital state follows a Markov chain and determines the mean and standard deviation of parental income.

The model incorporates the following ways in which the two groups may differ. First, the ability of parents with equal average lifetime earnings to invest in children's human capital depends on the variation of their income during childhood. Important factors, considered here, are the instability of families and the volatility of earnings due to transitory shocks. Black families are characterized by a higher probability of mothers and fathers to separate, and a lower probability of the mother to get re-married and replace the absent father. In addition, earnings of black parents are more volatile than those of white parents.

Second, the model permits the effect of parental investments on education outcomes to differ. The magnitude of the effect of the parental investment is influenced by monetary and non-monetary schooling costs and technology parameters. Differences in these factors might reflect disparities in school quality and neighborhoods. Third, the model allows for the possibility of statistical discrimination: lower expected labor market returns could reduce the incentive to invest in children's human capital. Finally, the model does not rule out variations in preferences.

I estimate the model using data from the Panel Study of Income Dynamics which allows me to observe parental lifecycles as well as child outcomes. The estimation proceeds in two steps. First, I estimate the parental income distributions and their evolution over the childhood years. I then simulate child outcomes given the parental income processes and match the simulated moments to the moments obtained from my dataset to recover the parameters. The parameter estimates together with the parental income process for both groups allow me to assess the relative contributions of the factors described earlier in explaining the racial differences in earnings mobility.

The paper is organized as follows. The model is presented in the next section, and its implementation is described in section **??**. A discussion of the data follows in section **??**. Section **??** describes the estimation procedure and section **??** presents and interprets the results. The final section concludes.

2 A Model of Life-Cycle Investments in Children

This is a dynamic model of parental investments in children's human capital. The parents are joint decision makers when both mother and father are present. If parents separate, the mother becomes the household head and makes all investment decisions. Parents have one child. The parental life-cycle starts with the birth of the child and ends when the child retires. Time is discrete and measured by the age of the child. Parents care about household consumption and the future earnings of their child. They can invest in the child until he is 16 years old, at which point his human capital endowment is fixed. Given his human capital the child now chooses the age a at which to drop out of school and to start employment. The time line is shown in figure **??**.

Human capital production depends on the child's current human capital stock and the parental investments i_t:

$$h_{t+1} = \left(h_t^{\varphi} + \varrho\, i_t^{\varphi}\right)^{\frac{1}{\varphi}} \quad \text{for } t < 16 \tag{1a}$$

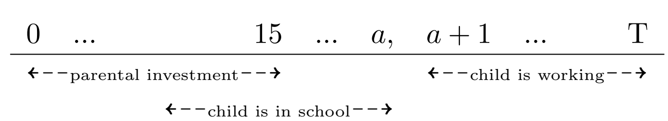
$$H = \left(\sum_{\tau=0}^{15} \varrho\, i_\tau^{\varphi}\right)^{\frac{1}{\varphi}} \tag{1b}$$

with $h_0 = 0$, $\sum \varrho \leq 1$ and $\varphi < 1$.

This CES specification assumes complementarities between parental investments in all childhood years. The productivity of the parental investment at any age $t < 16$ depends on previous and future human capital investments. This implies that the timing of parents' investments matters; for example parents cannot easily mitigate the effects of lacking early childhood investments by spending a lot when the child enters 10th grade. And the variance of parental income plays an important part in addition to mean income.[4]

[4]Note that $\left(\sum_{\tau=0}^{15} \varrho\, i_\tau^{\varphi}\right)^{\frac{1}{\varphi}} \leq \sum_{\tau=0}^{15} \varrho\, i_\tau$

Figure 1: Time line



The child can leave school at ages $a \, \epsilon A$, where A is a finite set of ages $a \geq 16$. Additional time spent in school increases his educational attainment. At age $a+1$ the child starts to work and from then on earns a wage which depends on his education, his human capital, and his labor market experience $(t-a-1)$, and is subject to iid wage shocks (ξ_t):

$$w_t = w(H, a, t, \xi_t) \tag{2}$$

Thus earnings are a function of standard wage determination factors.

Given his human capital, the child chooses the drop-out age to maximize the sum of his expected lifetime utility from earnings, less the cost of remaining in school. Let $W(H, a)$ denote the expected lifetime utility from earnings with schooling a and human capital H which is given by:

$$W(H, a) = \mathrm{E} \sum_{\tau=a+1}^{T} \delta^{\tau-16} U\big(w_\tau\big),$$

where U is a concave utility function and the expectation is taken over the wage shocks ξ_τ. Lifetime utility is assumed to be increasing in a.

The cost of schooling is denoted by $k(H, a)$. The cost of schooling includes monetary and non-monetary costs of achieving a and is normalized such that $k(H, \min(a)) = 0$. Note that an individual has to achieve a before he can attain $a+1$, hence the cost $k(H, a+1)$ must contain the cost of achieving a and the schooling cost is necessarily increasing in a. I also assume that the schooling cost is decreasing in human capital, $\frac{\partial k}{\partial H} \leq 0$. The idea is that higher human capital makes studying easier and enables children to receive scholarships or other outside support. In addition, each child has an individual distaste for studying η, which scales the cost of schooling up or down. The total utility from choosing a is given by:

$$v(a, H) = -k(H, a)e^{\eta} + W(H, a) \tag{3}$$

Parents do not observe the child's taste shock. But they know its distribution in the population and they can calculate the distribution of $a^* = \text{argmax } v(a)$ conditional on their human capital investments. I denote the probability of each a by $pr(a^* = a|H)$.

Parents' investment potential depends on their income, they face an exogenous income process $\{y_t(X, z_t)\}_{t=0}^{T}$, with:

$$y_t \sim F\big(\overline{y}(X, z_t), \sigma_y(X, z_t)\big) \tag{4}$$

The period realization of income is drawn from a distribution that depends on the parent's predetermined individual characteristics X and the income state, denoted by z_t. The income state is Markovian, and thus the probability distribution of the time t realizations of the state is conditional on the $t-1$ realization only.

Given their income process (**??**), the human capital technology (**??**), and $pr(a^* = a|H)$, determined by (**??**), parents choose investments in their child $\{i_t\}_{t=0}^{15}$ to maximize their lifetime utility from consumption and the child's earnings:

$$\begin{aligned} \max_{\{c_t, i_t\}_{t=0}^{T}} \quad & E\Big(\sum_{t=0}^{T} \delta^t \, U\big(c_t\big) + \delta^{16} \, \lambda W\big(H, a^*\big)\Big| X, z_0\Big) \\ \text{s.t.} \quad & c_t = y_t(X, z_t) - i_t \\ & H = \Big(\sum_{\tau=0}^{15} \varrho \, i_\tau^{\varphi}\Big)^{\frac{1}{\varphi}} \\ & a^* = \text{argmax } v(a, H) \end{aligned} \tag{5}$$

Parents evaluate the child's earnings and household consumption using the same concave utility function $U(\cdot)$, but they weight the utility their receive from the child's earnings by a factor λ.

The problem can be written in recursive form. The value of parenthood in period t, given the realization of the earnings state z_t and the current human capital stock h_t, equals the maximum of the parents' period consumption utility and their expected future value from optimal investment in their child:

$$V(t, h_t, z_t) = \max_{i_t} \Big\{ U(y_t - i_t) + \delta \mathrm{E}\Big(V\big(t+1, h_{t+1}, z_{t+1}\big)\Big| h_t, z_t\Big) \Big\} \tag{6a}$$

with terminal value at age 16:

$$V(16, H, z_{16}) = \mathrm{E}\Big(\sum_{t=16}^{T} \delta^{t-16} U(y_t) + \lambda W(H, a^*) \Big| H, z_{16} \Big). \tag{6b}$$

Because the parental investment is no longer productive after period 15, the de facto terminal value is given by the expected lifetime utility at $t = 16$. The optimal investment in each period t satisfies:

$$U'(y_t - i_t) \geq \frac{\partial h_{t+1}}{\partial i_t} \, \delta E_t V'(t+1, h_{t+1}, z_{t+1}) \tag{7}$$

or:

$$U'(y_t - i_t) \geq \delta^{16-t} \lambda \mathrm{E}_t \Big\{ \frac{\partial H}{\partial i_t} \Big(\sum_{a \epsilon A} pr(a^* = a|H) W'(H, a) + \frac{\partial pr(a^* = a|H)}{\partial H} W(H, a) \Big) \Big\}.$$

The marginal benefit of parents' investment today is the marginal effect on the expected lifetime utility from the child's earnings. This effect, given by the RHS of (**??**), is increasing in the weight on the utility from child earnings λ and the marginal productivity of the current investment $\frac{\partial H}{\partial i_t}$. The marginal productivity is increasing in the investments parents have made in previous years and in the ones they are expected to make in future childhood periods due to complementarities in human capital production. Furthermore, the marginal benefit of the current investment depends on the expected effect of human capital on the child's schooling outcomes and the returns to schooling.

The marginal cost of investing in children's human capital is given by the marginal decrease in consumption utility. This cost is larger the smaller the income realization y_t. All else equal, persistence in earnings over generations is generated by the effect of mean income on human capital investments. Parents with consistently higher income realizations are able to make higher investments in their child's human capital. In this case, outcomes for children with equally well off parents only vary randomly due to differences in the children's taste shocks. If we allow for variations in preferences, schooling costs, returns to schooling and the variance of income between parents with the same mean income, the intergenerational transmission of earnings experienced by the groups can differ. The next section details how the model is implemented to compare the intergenerational mobility experiences of blacks and whites in the US.

3 Implementation

3.1 Parameterization

Utility:

$$U(c_t) = \frac{c_t^{1-\gamma}}{1-\gamma} \tag{8}$$

Earnings Determination:

$$ln(w_t) = ln(H) + r_s + \beta_1(t - a^* - 1) + \beta_2(t - a^* - 1)^2 + \xi_t \quad \text{for } t \geq 16 \tag{9}$$

Wage determination is standard, except for the explicit incorporation of human capital which is unobserved to the econometrician. The return to school is denoted by r_s with $s = 1, ..4$ and corresponding "drop-out" ages $a = 16, 18, 20, 22$ and experience given by $t - a^* - 1$. The four schooling levels equal:

$s = 1$ High school drop-out

$s = 2$ High school graduate

$s = 3$ Some college, associate degree

$s = 4$ College, bachelor and graduate degrees

To simplify notation I will refer to each possible a^* by its corresponding education index s. The ξ_t are iid normal wage shocks.

Schooling Cost Function:

$$k(H, s) = k_s H^{-\kappa} \tag{10}$$

I assume that the schooling cost is multiplicatively separable in a constant attainment specific cost k_s and a decreasing function of H.

Utility from schooling level s:

$$v(s) = -k_s H^{-\kappa} e^{\eta} + W(H,s) \tag{11}$$

with $k_1 = 0$, and $\eta \sim N(0,1)$. In addition I make the following assumption:

$$\frac{\omega_s - \omega_{s-1}}{\omega_{s+1} - \omega_s} > \frac{k_s - k_{s-1}}{k_{s+1} - k_s} \quad \text{for } s = 2,3 \tag{$A_{ordered}$}$$

where $\omega_s = \frac{W(H,s)}{H^{1-\gamma}}$ is the expected lifetime return to schooling and experience with education level equal to s. This condition guarantees that this is an ordered choice problem with a unique solution for every taste shock. The condition always holds for convex cost and concave lifetime utility of earnings but is a weaker assumption than concavity of $W(H,a)$ and thus allows convexity in lifetime returns to education. Notice that this condition must hold if $a = a^*$ for any η.[5] Thus if **??** was violated at some a, no one would choose this education level. Since all the education levels I assume in the implementation are in fact chosen, this is not a restrictive assumption. Given the normality assumption and condition **??** we can obtain an analytic solution for the schooling probabilities. Let $R_s \equiv \frac{\omega_{s+1}-\omega_s}{k_{s+1}-k_s}$ and $\pi = 1-\gamma+\kappa$, then the child chooses alternative s if $R_s H^{\pi} \leq e^{\eta} \leq R_{s-1} H^{\pi}$, and the choice probabilities are equal to:

$$pr(s = n|H) = \begin{cases} 1 - \Phi\big(lnR_1 + \pi\ lnH\big) & \text{for } n = 1 \\ \Phi\big(lnR_{n-1} + \pi\ lnH\big) - \Phi\big(lnR_n + \pi\ lnH\big) & \text{for } n = 2,3 \\ \Phi\big(lnR_3 + \pi\ lnH\big) & \text{for } n = 4 \end{cases}$$

The cut-offs $lnR_1 - lnR_3$ and π determine the magnitude of the marginal effect of parental investments on the likelihood of obtaining successively higher degrees. Differences in these parameters yield different investment choices for parents with equivalent income realizations. Suppose the effect of parents is weaker for blacks, for instance as a results of higher k_s, the monetary and non-monetary cost of education, then black parents invest less because they face a lower return

[5] An individual with η' chooses a' over $a'+1$ and $a'-1$ iff $v(a') > v(a'+1)$ and $v(a') > v(a'-1)$ $\Leftrightarrow$ $\frac{W(H,a')-W(H,a'-1)}{k(H,a')-k(H,a'-1)} > \eta > \frac{W(H,a'+1)-W(H,a')}{k(H,a'+1)-k(H,a')}$

to their investment than otherwise equivalent white parents. Black children in this case not only face a different reward structure but also obtain less human capital investments from their parents. Both of these make it less likely for them to make it into the higher education groups.

3.2 The Parental Income Process

The model maps a distribution of parental earnings and its evolution into children's outcomes, given the technology of human capital production, returns in the labor market, parental influence on schooling choices, and preferences. Variations in child outcomes can arise for the same parameter values if the parental income process differs.

Parental earnings are the combined earnings of the child's parents. I assume that if parents divorce or separate the father leaves the household. Thus the size of parental earnings available for investments depends on the mother's "marital" state and the income state z_t can take two values: $z_t = 1$ married or co-residing with father, and $z_t = 2$ divorced or not co-residing with father.[6] The state dependent mean of parental earnings, given the parents' predetermined characteristics X, equals:

$$\overline{y}(X, z_t) = \overline{w}_m(X, z_t) + I(z_t = 1)\overline{w}_f(X) + I(z_t = 2)\alpha\, \overline{w}_f(X) \tag{12}$$

Parental income is the sum of the mother's earnings, w_m, and the father's earnings w_f if he is present in the household, or a fraction α of the absent father's earnings if he is not. If the mother has remarried, her husband contributes his earnings, instead of the absent father[7]. The marital state evolves according to the transition probabilities $\{p(z'|z)\}_{z,z'=1,2}$. In addition to state dependent contributions of male caregivers I also allow for the mother's mean earnings to depend on her marital state, as she might earn less after separating from her husband because she has to cut down on hours to take care of her child[8]. The income realization is also determined by a transitory shock, which is drawn from a normal distribution with mean equal to zero and state dependent

[6] I am not distinguishing between marriage to the father or to another person. Co-residing fathers are included in state 1 though, but not live-in boyfriends.

[7] Alternatively I could assume the absent father keeps contributing a fraction α and the husband contributes $1 - \alpha$

[8] Alternatively she might enter the labor force if she had been staying at home to compensate for lost earnings of her husband. In this case her earnings would increase

variance:

$$ln(w_{pt}) = ln\big(\overline{w}_p(X, z_t)\big) + \epsilon_t \tag{13}$$

with $\epsilon_{pt} \sim N(0, \sigma_{p\epsilon}(z_t))$, p=m,f.[9]

Mothers' and fathers' mean earnings are predetermined by their exogenous characteristics X. But, with the exception of race, parental characteristics play no other role in this model apart from determining earnings, which I observe directly. Therefore parents are fully characterized by their mean earnings, their race, and the parameters of the model, which allows a direct comparison of intergenerational mobility for children of parents with equal mean income from both racial groups.

To make a solution to the model computationally feasible, I draw parental mean earnings using systematic sampling from the empirical earnings distributions for mothers and fathers estimated from the PSID dataset.[10] The parameters determining the evolution of earnings are given by the income state transition probabilities and the variances of the transitory shocks, which I allow to differ between blacks (b) and whites (w):

$$\vartheta_P = \big[\{\ p_w(z'|z), p_b(z'|z), \sigma_{\epsilon pw}(z), \sigma_{\epsilon pb}(z)\}_{z=1,2\ p=m,f}\big] \tag{14}$$

I estimate these parameters directly from my PSID dataset. The parameter α which determines the contribution of absent fathers and non-father husbands is estimated along the rest of the model's parameters as described below.

[9] Note that the distribution of the sum of lognormal variables does not have a closed form solution. There exist several approximations, but I do not need to be concerned with the exact form of the combined distribution since I can simulate a solution for two independent draws for each parent.

[10] I approximate the earnings distributions by a number of mean percentile points. For simplicity I assume a mother occupies the same percentile in the married and unmarried distributions and that she does not get to redraw her husbands mean earnings after remarriage. Including the possibility of improving or worsening of the parental type through remarriage would mean adding the father type as an additional state variable. This might be considered in future versions.

4 The Data

4.1 Description of the PSID dataset

The Panel Study of Income Dynamics is a longitudinal survey conducted by the Survey Research Center at the Institute for Social Research, University of Michigan[11]. The study has been following an initial sample of around 4,800 families since 1968. The 1968 core sample combines a nationally representative sample of families that was drawn by the Survey Research Center, the SRC sample, and an over-sample of low-income families selected from the Survey of Economic Opportunity of the Census, the SEO sample.[12] Individuals from PSID families were interviewed annually from 1968-1996 and biannually since 1997. Split-off families, households started by original sample members or their children (or grandchildren), were absorbed into the survey and followed. The longitudinal panel of families therefore includes both observations on parent families and on child families, and this allows me to observe parental income during childhood as well as the outcomes of adult children who have started their own households.

I begin with the complete panel from the 1968-2005 family data files and limit my sample to individuals and their families who are either black or white and drop all other ethnicities.[13] From this I construct a dataset of mothers and her children and each child's father using the 2005 parent identification file. And I link mothers to her husbands' data using the 1985-2005 marriage history file, which gives data on retrospective histories of marriages, including year of marriage and separation and the husbands' identifers to locate their data. I regard each mother child pair as a family.[14] The data of all fathers who are sample members is included in the dataset, whether he is present in the mother-child household or not. Husbands, other than fathers, and their observations

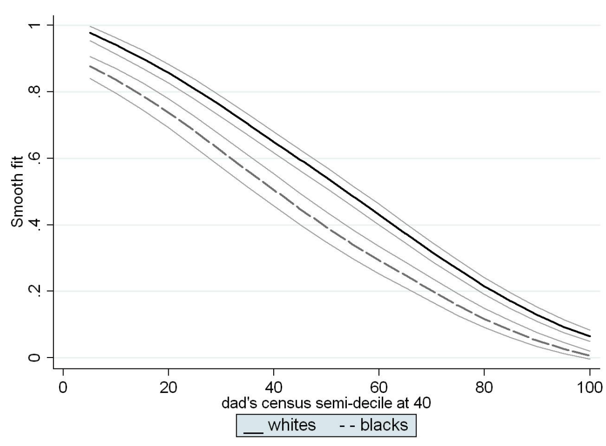
[11]"The Panel Study of Income Dynamics is primarily sponsored by the National Science Foundation, the National Institute of Aging, and the National Institute of Child Health and Human Development and is conducted by the University of Michigan."

[12]The SRC sample was drawn with equal probability from the 48 contiguous states. The SEO sample was drawn from standard metropolitan statistical ares in the North and non-metropolitan areas in the South. In 1997 when the PSID switched to biannual interviews and added an immigrant sample this subsample was reduced by two thirds in an effort to save funds. All white families were dropped from the SEO sample and black families were subsampled. The PSID provides individual weights through their 1968-2005 individual data files that account for sample selection and attrition which I use in the regressions in section **??**.

[13]A total of 25125 individuals, 16046 whites and 9079 blacks.

[14]In the calculation of standard errors this will be considered. The size of the sample does not allow me to focus on one child families.

Figure 2: predicted upward probability by dad's percentile



are only included for the years that they were married to the mother.

Data on parental earnings is reported in table **??**. The data shows that Black mothers and fathers earn less on average than whites. Single mothers of both races are poorer on average than married mothers. While single women, who are not mothers, tend to have higher earnings than married women, because they tend to work more, single *mothers* are likely to be constrained in the amount of time they are able to work. Table **??** shows the distribution of black mothers and fathers across quintiles of the mother and father earnings distributions. In line with their lower mean earnings, blacks are more concentrated at the bottom of the overall income distribution.

4.2 The Black-White Mobility Gap

Previous studies have shown that black families are less likely to move out of the bottom quintile of the family income distribution and more likely to fall out of the top quintile than white families (**?**) and that black sons experience less upward mobility in earnings compared to white sons in relation to their parents' position in the family income distribution (**??**).

I confirm these facts using intergenerational data on earnings from the PSID. I compare fathers' and sons' earings at the same stage of their lifecycle by predicting earnings at age 40, and I compare the relative positions they have attained in their generation's earnings distribution by matching individuals' earnings to percentile boundaries obtained from large representative samples of 40-year-olds from the 1960-2000 Censi.[15] [16] As a measure of relative position I use semi-deciles (5 % steps), which account for smaller movements in relative position than quintiles. Because black men tend to be poorer, they might be concentrated at the bottom of the individual quintile, which increases the probability of their sons moving into the quintile below. Using smaller bins mitigates this effect. Upward mobility is indicated by a dummy variable that takes the value 1 if the son has surpassed his father's percentile in his generations income distribution and zero otherwise. I estimate a probit regression to predict the probability to move above the father's position, controlling for fathers' percentile. Figure **??** plots the predicted probabilities by father's percentile and the 95% confidence band. The relationship between father's percentile and upward probability is negative since it gets harder to surpass successively higher percentiles. At every percentile the probabilities for blacks are significantly different and below those for whites.

Next, I estimate a standard log-linear earnings regression to which I add a dummy variable for black sons and an interaction term of the dummy with their fathers' earnings. Table **??** reports the estimates of the intergenerational elasticity of earnings. For white father-son pairs the estimated IGE of 0.36 is well within the expected range for the US[17], but for black pairs, with an estimated coefficient on fathers earnings of only 0.2, it is significantly lower.

I check the robustness of these results by adding dummy variables for location and number of siblings.[18] The results remain virtually unchanged as shown in columns (3) and (5) of table **??** in the appendix. In addition, I estimate the more standard version of the intergenerational regression, following **?**, which uses earnings observations for fathers at the beginning of the sample period in 1968 and for sons at the end of the sample, here 1996.[19] I add the son's and father's age and age squared to control for both men's lifecycle effects on earnings. Column 1 of table **??** reports the estimates. With an estimate of 0.48 the IGE for whites is somewhat higher using this

[15]Note that while the PSID provides weights that account for the different selection probabilities of its two samples and for sample attrition constructing samples of 40 year olds to estimate their earnings distribution would lead to tiny sample sizes.

[16]The PSID earnings data and the census data are described in appendix **??**.

[17]See **?** for a summary table with estimates obtained in the literature.

[18]Location is relevant since the Southern States of the US have a larger black population and are also poorer on average. The number of siblings might change the results if black families tend to be larger and the number of children affects the intergenerational elasticity.

[19]I use the earnings of all sons present in 1996 and their fathers average earnings for the beginning of the PSID sample (1968-1975). The 1996 sample is the most recent before the PSID reduces its sample in 1997 due to funding constraints.

Table 1: ***Intergenerational Regression***

Dependent Variable: Son's Earnings at 40	Coef.	(Std. err.)
Father's Earnings at 40	0.358***	(0.032)
Father's Earnings at 40 x black	-0.154**	(0.062)
Black	1.186*	(0.642)
Constant	6.658***	(0.348)
R-squared		0.166
N. of cases		2986

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

standard errors are clustered around family. Controls for age and age^2 *of fathers and sons are included.*

specification[20], but the coefficient on black fathers' earnings is again around 0.2, confirming the previous estimates.

This evidence shows that the predictive power of fathers' income is significantly lower for blacks than it is for whites. The interpretation of the IGE as a measure of mobility is only valid if the simple log-linear relationship between fathers' and sons' income sufficiently characterizes the intergenerational transmission mechanism.[21] This does not seem to be the case, by comparing the relative positions of black fathers and sons, and white fathers and sons, me and others have found that, in fact, blacks are less upwardly mobile at every parental percentile of the distribution.

In the following analysis I go beyond a comparison of aggregate measures of parental income to analyze intergenerational transmission. My model incorporates dynamic aspects of investment in children by specifically taking into account the evolution of parental earnings during childhood. Furthermore, the structural model allows a comparison of the contributions of possible differences in preferences, returns to school and schooling costs in an explanation of the mobility gap. Before I present the estimation results of the structural model, the next section details the estimation procedure.

[20] Solon's estimate for the 1984 SRC sample, excluding the black dummy variables, is 0.41. Using the SRC and SEO sample for 1984 it is somewhat lower, 0.36.

[21] Note that, because the constant term in the regression is larger for blacks, black sons are not reverting to a lower mean income than white sons, which could reconcile the smaller coefficient with the facts on relative intergenerational mobility

5 Estimation Procedure

The model is estimated in two steps. First, estimates of the parents' earnings distributions and the parameters of the income process, which were described in section **??**, are obtained directly from the data. Then the rest of the parameters are estimated by simulated methods of moments.

The parameters of the model, apart from those contained in ϑ_P, are the preference parameters, the technology parameters, schooling costs and returns to schooling. Preferences are determined by λ, the weight on the utility from child earnings, γ, the curvature of the utility function, and α, the contribution of absent fathers and stepfathers. The human capital technology depends on the CES production function parameter φ and on κ, which determines the effectiveness of human capital in reducing schooling costs. The paramters determining earnings are the returns to education r_s, the returns to experience, determined by $\beta_1 \text{and} \beta_2$, and the variance of the wage shocks, σ_ξ. Finally, there are the monetary and non-monetary schooling cost parameters k_s. Paramters that are not estimated are ϱ, the productivity weights in human capital production, which are set equal across all years. And the discount rate δ, which I fix at 0.98. The 16x2 parameters to be estimated in this second step are collected in the parameter vector θ:

$$\theta = [\lambda_j, \gamma_j, \alpha_j, \varphi_j, \{r_{sj}\}_{s=1..4}, \beta_{1,j}, \beta_{2,j}, \sigma_{\xi,j}, \{k_{sj}\}_{s=2}^{4}, \kappa_j] \tag{15}$$

with $j = b, w$.

The estimation routine chooses the parameter vector $\widehat{\theta}$ to minimize the squared distance between the simulated moments and the data moments. Let the vector of simulated moments be given by $\mu(\theta)$ and the data moments by $\widehat{\mu}$, then the objective function to be minimized by the estimation procedure is:

$$\min_{\theta} \ \big(\widehat{\mu} - \mu(\theta)\big)' W^{-1} \big(\widehat{\mu} - \mu(\theta)\big) \tag{16}$$

where W is a weighting matrix, consisting of the diagonal elements of the empirical variance-covariance matrix of the data moments.

At each iteration, starting at a candidate vector of parameter values θ_0, simulated moments

Table 2: ***Moments***

child wages
means and standard deviations of:
total earnings at ages 20,25,..40 [10x2]
1st differences of earnings [8x2]
earnings by schooling at ages 20,25,..40 [36x2]
1st differences of earnings by schooling [28x2]
earnings by parent quintile [10x2]
schooling outcomes
schooling proportions [4x2]
intergenerational correlations
corr of child wage at 40 and parent wage during childhood [1x2]
corr of child wage at 40 and father's wage at age 40 [1x2]
corr of child wage and coeff. of variation of parent wage during childhood [1x2]
correlation absent and present fathers [2x2]
intergenerational mobility
average probability of upward mobility by father's quintile [5x2]

are computed by proceeding as follows: The model is solved recursively starting in period T, given the terminal value (**??**). For each parental mean earnings draw from the estimated earnings distributions the model is solved for a number of discrete human capital states on an exponential grid, for a number of transitory wage shocks and for each marital state. The solution in each period t is used to calculate the expected value in $t-1$ conditional on the earnings state and human capital grid point, $E_{t-1}\{V(t, H_t, z_t)|H_{t-1}, z_{t-1}\}$, by averaging over the wage shocks and applying the transitions probabilities $p_{z'|z}$ for the marital states.

Then, given the expected values calculated in the previous step, the model is solved forward starting at the initial state. This is done for a population of parents that reflects the empirical earnings distributions, proportions of blacks and whites and married and unmarried mothers. For each member of this population wage shocks and marital states are drawn in accordance with the parameters of the parental wage process. Finally, given these optimal investment sequences, schooling outcomes for each child can be predicted and used to calculate mean wages, aggregate schooling proportions and other moments.

A list of moments is shown in table **??**. For each general moment I indicate the number of individual moments in square brackets.

Table 3: ***Parameters of the parental income process***

		Blacks	**Whites**
marriage transitions over the childhood			
married-married	$p(1\|1)$	92.19	96.72
married-single	$p(2\|1)$	7.81	3.06
single-married	$p(1\|2)$	17.05	26.72
single-single	$p(2\|2)$	82.95	73.28
standard deviations transitory shocks			
married mothers	$\sigma_{\epsilon m}(1)$	0.6408	0.4658
single mothers	$\sigma_{\epsilon m}(2)$	0.8012	0.7403
fathers	$\sigma_{\epsilon f}$	0.5429	0.4495
state when child is one years old			
married	$z_0 = 1$ %	60.56	93.49
single	$z_0 = 2$ %	39.44	6.51

6 Results

6.1 Parameter Estimates

Parameter estimates of the parental income process are reported in table **??**. White mothers are more likely to stay married and less likely to remain single mothers. Each year, black mothers are around 4% more likely to separate from their husbands and about 10% less likely to (re)marry.

Single motherhood is not only more persistent for black mothers relative to white mothers, black women are also more likely to start out as single mothers. In addition, the variance of parental income during childhood is higher for black parents. For both groups the variance is higher for single mothers, but because black mothers are more likely to be separated, the difference in the overall variation of parental income during childhood is even larger.

I use the parameter estimates of the parental income process in the simulation based estimation of the remaining model parameters. The estimates for both groups are reported in table **??**. In contrary to the estimates of the marital transition probabilities and the variances of the transitory shocks, these parameter estimates are very similar for both groups. The estimates indicate slight differences in preferences. Black parents place a weight of about 1/2 on the utility from child earnings, while white parents place a weight of about 0.44. The contribution of absent fathers is equivalent for both groups. The CES production technology for human capital exhibits stronger complementarities for whites than for blacks, which also translates into a stronger effect of the

Table 4: ***Parameter Estimates***

	Blacks	**Whites**
Preferences		
λ	0.513	0.4434
γ	0.4685	0.3932
α	0.0348	0.031
Technology		
φ	0.5293	0.4341
κ	0.1008	0.1165
Schooling Costs		
k_1	8.925	8.6807
k_2	55,594	56,771
k_3	272,738	240,620
Earnings		
r_1	7.518	7,742
r_2	9.294	9,048
r_3	11,641	10,934
r_4	15,021	13,873
β_1	0.0478	0.0662
β_2	-0.0008	-0.0014
σ_ξ	0.4155	0.3481

parental investment on human capital. There is also a slightly larger effect of the parental human capital investment in the schooling cost function for white parents. Furthermore, the cost of attaining a college degree, k_3 is higher for black sons than for white sons, while the costs of achieving high school graduation or attending college without getting at least a bachelor's degree is nearly equivalent.

The estimated returns to school imply higher returns to achieving high school and college degrees for blacks. Note that this means that the incentive for black parents to invest in their child's human capital, all else equal, is higher than for white parents, and this would decrease the mobility gap.

6.2 Model Fit

Table **??** displays a subset of the moments to illustrate the overall fit of the model. The model fits the education proportions reasonably well, it slightly underestimates the proportion of individuals attaining a college degree, and overestimates the ones with only a High School diploma for both groups. The model is able to generate the mobility gap between blacks and whites. Both the intergenerational elasticity and the probabilities of upward mobility are lower for black sons. Pre-

Table 5: ***Model Fit***

	Data		Model	
	Blacks	**Whites**	**Blacks**	**Whites**
Schooling Proportions				
no High School	0.2480	0.1534	0.2411	0.2177
High School	0.4571	0.3850	0.5067	0.4251
some College	0.2263	0.2683	0.2170	0.2341
College	0.0686	0.1931	0.0352	0.1231
Mean Earnings at 30				
All Schooling Levels	26,055	43,038	21,993	38,159
no High School	15,487	26,157	11,838	23,163
High School	23,864	35,751	20,538	33,072
some College	28,377	43,318	32,612	47,002
College	40,733	56,008	43,920	65,227
Mean Earnings at 40				
All Schooling Levels	34,634	62,081	27,945	48,278
no High School	18,662	31,266	13,952	26,315
High School	32,437	42,182	25,129	40,343
some College	37,025	53,932	43,175	61,027
College	50,266	91,876	67,323	90,081
Intergenerational Elasticity				
IGE	0.1954	0.3365	0.4629	0.5757
IGE Gap	0.1411		0.1129	
Upward Prob. by Father's Quintile				
Bottom	0.7835	0.8898	0.7911	0.8460
Second	0.6283	0.7711	0.4312	0.6481
Middle	0.4376	0.6082	0.5089	0.5575
Fourth	0.2696	0.4192	0.2677	0.3126
Top	0.1544	0.2487	0.0930	0.3900
Mobility Gap	0.6636		0.6625	

dicted elasticities and probabilities to attain a higher income percentile than the father, by father's quintile, are shown in the bottom half of table **??**. The IGE estimates are higher than in the data but the difference ("IGE Gap") between the black and white coefficients are close, 0.14 in the data and 0.11 predicted by the model. This means that the model is able to explain about 80% of the difference in the IGEs.

Let me define the mobility gap between black sons and white sons as the difference between the two groups' curves of predicted upward mobility probabilities. Figure **??** plots the probabilities predicted by the model conditional on the fathers' semi deciles[22]. Here, I approximate this gap by the sum of the differences over fathers' quintiles. While the model does not fit all of the upward

[22]The 95% interval is shown in dashed lines.

mobility proportions for both groups, its prediction of the mobility gap matches the gap observed in the data, as shown in the last row of table ??.

The next subsection analyzes whether the estimated differences in the parameters are able to explain part of the mobility gap, and how much of the gap can be accounted for by the differences in the parental income process.

6.3 Analysis

I analyze contribution of the individual racial disparities to an explanation of the mobility gap by performing seven counterfactual experiments. I successively equalize the following
between the groups:

1. The initial marital state
2. The martial state transition probabilities
3. The initial marital state and the martial state transition probabilities
4. The variances of the transitory shocks
5. Both 2. and 4. (e.g. equal income processes)
6. Schooling costs and κ
7. All parameter, except for those of the parental income process

For each of these I predict the intergenerational elasticity and the upward mobility probabilities. I then compare the gaps obtained across the experiments, and calculate the % of the empirical gap that can be attributed to the individual component which had been shut off. Figures ?? to ?? depict the graphs of the predicted upward mobility probabilities. Table ?? shows the IGE gaps and the mobility gaps, and the implied percentages explained.

The first experiment shows that the initial proportion of married mothers contributes to 19% of the explained mobility gap and 9% of the IGE differences. Thus the initial proportion of absent fathers unsurprisingly contributes to black sons falling behind. But this is not the sole important explanatory factor. The differences in the transitions from marriage to separation, without the initial proportion of unmarried mothers, contribute almost 30% to the explanation of the IGE gap and 60% to the mobility gap. The importance of differences in marriage patterns is highlighted in

Table 6: ***Predicted Mobility Differences***

	data	model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IGE Gap	0.1411	0.1129	0.1025	0.0804	0.0714	0.1145	0.0789	0.1107	0.0909
% explained		80.01	9.21	28.79	36.76	0	30.12	1.95	19.49
Mobility Gap	0.6636	0.6625	0.5388	0.2729	0.0961	0.5970	0.1356	0.6488	0.9284
"% explained"		99.83	18.67	58.81	85.49	10	79.53	2.07	-

the third counterfactual, when I shut-off both of the previous factors. They generate 85% of the explained mobility gap and almost 40 % of the IGE gap.

The variances of the transitory shocks to parents' earnings during the childhood alone, contribute little to an explanation of the gaps.But, shutting off both the marital states and the variances eliminates 30% the differences in the IGEs and reduces the mobility gap by 80%. The marital states have two effects, first they directly lower the contribution of the father, and second, mothers spend more time in the divorce state which has a higher variance (for both groups). Thus both the higher variance of income over the childhood and the differences in the marital states transitions mutually reinforce their negative effects on children's human capital.

Finally, I show the implications of equalizing the parameter estimates of θ between the two groups. First, in experiment number (6), I shut off the differences in schooling costs and κ, the coefficient on human capital in the cost function. This does hardly affects the mobility gap. Second, I set all the parameters of blacks equal to the ones obtained for whites. Recall that the estimated returns to school were higher for blacks, and since this increases the incentive for parents to invest in their child's human capital, turning off this advantage leads to an increase in the mobility gap as shown in the last column of table 6.

In summary, the results indicate that the black-white mobility gap can be explained by differences in the parental income process during childhood. And it is not generated by disparities in labor market returns or parental preferences.

Figure 3: predicted upward probability with estimated parameters

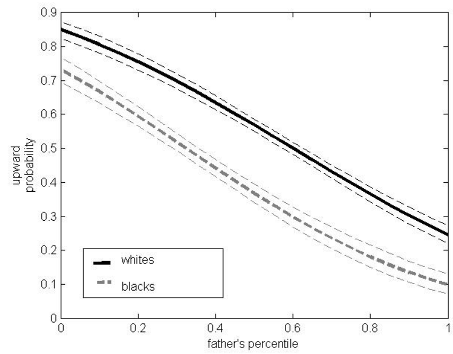


Figure 4: predicted upward probability, equal initial marital state (1)

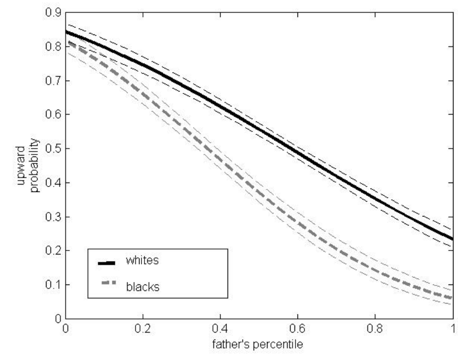


Figure 5: predicted upward probability, equal marital transitions (2)

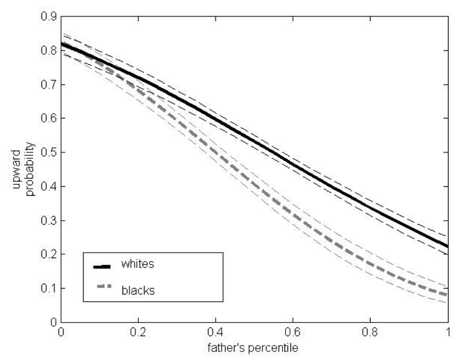


Figure 6: predicted upward probability, equal marital state and transitions (3)

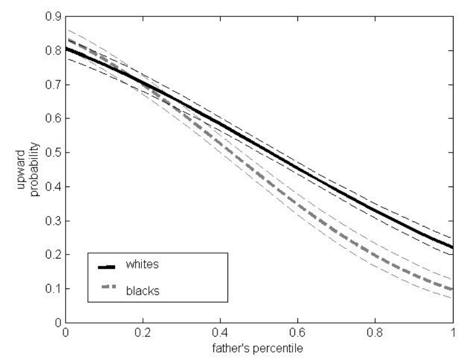


Figure 7: predicted upward probability, equal marital transitions and variances (5)

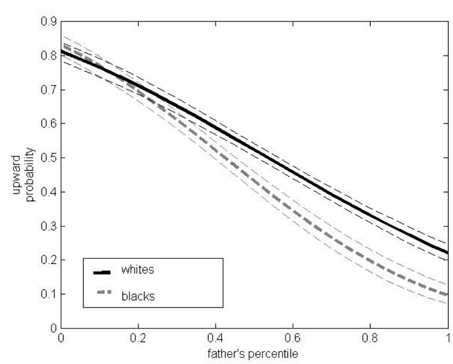
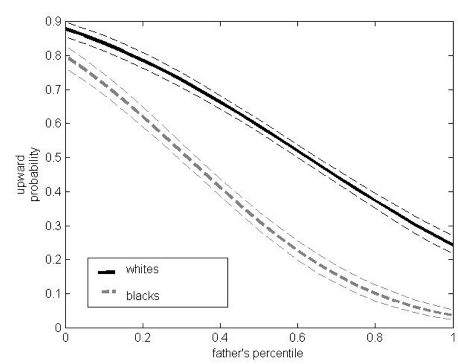


Figure 8: predicted upward probability, equal parameters in θ (7)



7 Conclusion

There is a significant gap in upward mobility between black and white sons. At every percentile of the last generation's earnings distribution, black sons are more likely to move down with respect to their fathers' position. In addition, the predictive power of fathers' income is significantly lower for blacks than it is for whites. In this paper I go beyond a comparison of aggregate measures of parental income to analyze the intergenerational transmission of earnings. I built a structural model of parental investments in children's human capital that incorporates dynamic aspects of investment in children. Furthermore, this structural model allows me to investigate several possible explanations for the mobility gap within the context of optimal investment behavior of parents.

I find that there are no differences in the valuation of future child earnings between the two groups. Furthermore, different estimates of the returns to education, which show in fact higher returns for blacks, and schooling costs cannot contribute to an explanation of the mobility gap. What drives the emergence of a gap in upward mobility and the weaker relationship between fathers' and sons' earnings are differences in parental income during childhood, which are due to the dissolution of families and transitory income shocks. I show evidence that black and white families differ in the volatility of their income and that this can account for the observed mobility gap between black father-son pairs and their white counterparts.

This paper focused on the contributions of parents to an explanation of the observed racial gaps. **?** was one of the first to stress that black children are not only disadvantaged because they have parents of poorer background but also because their social environment is made up of people who tend to be poorer and less educated than those most white children interact with. Future research will need to take into account that children of the two groups grow up in disparate environments, and investigate how this affects the influence parents have on the achievements of their children.

A Tables

Table A-1: ***Parent Characteristics***

Variable	Mean	Std. Dev.	N
All			
Earnings married mothers	21,069	19,362	1828
Earnings single mothers	17,211	14,906	833
Earnings fathers	46,222	32,896	2181
Blacks			
Earnings married mothers	18,630	14,413	553
Earnings single mothers	15,590	13,377	418
Earnings fathers	33,810	18,764	623
Whites			
Earnings married mothers	22,316	21,350	1293
Earnings single mothers	20,437	17,107	425
Earnings fathers	52,330	36,399	1578

Table A-2: ***Percent of Mother's and Fathers across Quintiles of the Earnings Distribution***

Blacks			**Father**			
Mother	Bottom	Second	Middle	Fourth	Top	Total
Bottom	10.3	3.8	2.7	1.9	0.7	19.4
Second	7.0	7.1	3.6	2.2	1.0	20.9
Middle	6.0	5.6	5.0	3.2	1.1	20.8
Fourth	3.9	5.3	4.6	4.9	1.9	20.7
Top	3.1	4.0	4.0	4.4	2.6	18.2
Total	30.3	25.9	19.9	16.6	7.3	100.0

Whites			**Father**			
Mother	Bottom	Second	Middle	Fourth	Top	Total
Bottom	4.0	3.1	3.2	2.8	3.3	16.4
Second	3.0	3.5	4.1	4.2	4.6	19.3
Middle	2.7	3.6	4.8	4.5	4.5	20.1
Fourth	2.2	4.0	3.7	5.0	5.2	20.2
Top	1.4	2.8	4.4	5.9	9.4	24.0
Total	13.4	17.0	20.3	22.3	27.0	100.0

Table A-3: ***Intergenerational Regressions***

Dependent Variable: Son's Earnings	(1) Coef./Std. err.	(2) Coef./Std. err.	(3) Coef./Std. err.	(4) Coef./Std. err.	(5) Coef./Std. err.	(6) Coef./Std. err.
Father's Earnings 68-75	0.476***		0.482***		0.477***	
	(0.050)		(0.054)		(0.050)	
Father's Earnings 68-75	-0.296***		-0.309***		-0.294***	
x black	(0.081)		(0.081)		(0.082)	
Father's Earnings at 40		0.358***		0.381***		0.357***
		(0.032)		(0.034)		(0.032)
Father's Earnings at 40		-0.154**		-0.190***		-0.157**
x black		(0.062)		(0.063)		(0.063)
Black	2.953***	1.186*	3.097***	1.554**	2.930***	1.225*
	(0.818)	(0.642)	(0.823)	(0.644)	(0.823)	(0.645)
South			-0.037	0.003		
			(0.068)	(0.038)		
Number of siblings					0.005	-0.008
					(0.014)	(0.008)
Constant	3.272***	6.658***	3.358***	6.419***	3.277***	6.697***
	(0.730)	(0.348)	(0.910)	(0.368)	(0.731)	(0.350)
R-squared	0.144	0.166	0.139	0.177	0.144	0.166
N. of cases	1507	2986	1378	2814	1507	2986

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

standard errors are clustered around family. Controls for age and age^2 of fathers and sons are included. Son's earnings is measure in 1996 for specifications (1), (3) and (5); it is predicted earnings at 40 for (2), (4) and (6).

B Earnings Predictions and Distributions

B.1 Predicted Earnings using the PSID

The PSID collects labor income for household heads and wives. Labor income is defined as the sum of several labor income components in addition to wages and salaries; these include bonuses, overtime, tips, commissions, professional practice and trade income, market gardening income, and miscellaneous labor income. Until 1994 it also included the labor part of farm and business incomes.[23] Labor parts of business incomes are reported separately for 1994-2005 and I add it back to labor incomes for these years. Labor income is top coded at 99,999 until 1982, at 999,999 until 1991, then at 9,999,999.

All earnings measures are in 2003 \$, adjusted using CPI data from the Bureau of Labor Statistic's website.

I estimate age-earnings profiles by regressing observed earnings on experience and experience squared, which is measured by age minus schooling, by race, gender and schooling (no high school, high school, some college, and college) and add individual fixed effects:

$$y_{it} = \gamma_i + \alpha_{0g} + \alpha_{1g} age_{it} + \alpha_{2g} age_{it}^2 + \alpha_{3g} age_{it}^3 + \alpha_{4g} age_{it}^4 + \epsilon_{it}$$

where $i \epsilon g$ and g includes 16 groups, for each race, gender and schooling level. I use the estimates of these profiles and the individual fixed effect to predict earnings for each individual. I then take predicted earnings at age 40 as my measure of income.

B.2 Earnings Percentiles from the Census

I obtain earnings data from the 1960-2000 Censi using the Minnesota Population Center's Integrated Public Use Microdata Series (**?**). I use the 1960 1% sample, the 1970 Form 2 State sample (1%), the 1980 5% sample and the 1990 and 2000 unweighted 1% samples. I chose these samples because

[23]The PSID calculates labor parts of farm and business income by allocating half of the income to asset income and the other half to labor income and splitting these evenly between heads and wives if the business is co-owned by both.

they are all unweighted representative samples.[24]

The Census reports respondent's annual wage and salary income for the previous calendar year. This also includes commissions, cash bonuses, tips, and other money income received from an employer but it does not include the labor parts of business and farm income. I thus adjust earnings by adding half of business and farm income, which is reported separately. This makes the labor income measure comparable to the one from the PSID, as described in appendix C.[25]

I construct semi-decile (5 % steps) boundaries for the distributions of male and female earnings at age 40 from each of the 1960-2000 Censi and match these percentiles to my PSID dataset. Individuals are matched to the Census year that is closest to the year when they were 40 years old. For most parents Census years 1960-1980 provide the best match, older parents are also matched to the 1960 census. All children who have not yet reached their 40th year will be matched to the 2000 census. I then determine each person's semi-decile using his predicted earnings at age 40 and the percentile boundaries from the relevant Census year and gender distribution.

[24] For a description of the sample designs used for various years and samples see http://usa.ipums.org/usa/chapter2/chapter2.shtml

[25] One remaining difference between the two measures is that professional practice income is included in business income in the Census but is part of labor income in the PSID.