CHANGES IN THE CHARACTERISTICS OF AMERICAN YOUTH: IMPLICATIONS FOR ADULT OUTCOMES

JOSEPH G. ALTONJI, PRASHANT BHARADWAJ & FABIAN LANGE†

ABSTRACT. We examine changes in the characteristics of American youth between the late 1970s and the late 1990s, with a focus on characteristics that matter for labor market success. We reweight the NLSY79 to look like the NLSY97 along a number of dimensions that are related to labor market success, including race, gender, parental background, education, test scores, and variables that capture whether individuals transition smoothly from school to work. We then use the reweighted sample to examine how changes in the distribution of observable skills affect employment and wages. We also use standard regression methods to assess the labor market consequences of differences between the two cohorts in skill indicators. Overall, we find that the current generation is more skilled than the previous one. Blacks and Hispanics have gained relative to whites and women have gained relative to men. However, skill differences within groups have increased considerably and overall, the skill distribution has widened. Shifts in parental education seem to generate many of the observed changes.

Date: **Revised August 2008**.

Altonji: Yale University, NBER and IZA; Bharadwaj: Yale University; Lange: Yale University and IZA. We are grateful to the Yale Economic Growth Center for research support. We thank Daniel Black, James Heckman, Patrick Kline, Paul LaFontaine, Costas Meghir, Robert Michael, Richard Mansfield, Derek Neal and seminar participants at the Bureau of Labor Statistics, Duke, the Institute for Poverty Research, NBER, Ohio State University, U. of Aarhus, University College London, U. of Washington, and the European Summer Symposium in Labour Economics (Sept 2007) for valuable comments. Thanks to Steven McClaskie for support with the NLSY data and to Daniel Segall for assistance with the AFQT data.

1. Introduction

Labor and growth economists typically consider the process of skill formation to be a primary driving force of both economic inequality and economic development. Consequently, the literature abounds with studies that investigate how overall skill formation contributes to growth and inequality.[1] However, while the central role of skill acquisition is well understood, relatively little is known about how young people today compare to their predecessors along various dimensions of skill. Without this knowledge there are many questions that we can not begin to address.

For example, how will the adult labor market outcomes of American youth compare to those of the previous generation? Will gaps between race and ethnic groups narrow or widen? How will other key outcomes, such as marriage, fertility and incarceration rates differ across generations? The answers to these questions hinge in part on broad changes in social processes, culture, government policy, and the economy that are very difficult to forecast decades in advance. However, the answers also depend on the distribution of cognitive and non-cognitive skills among today's youth, a distribution that is already partially observed. In particular, we can measure the parental background, race and ethnicity, cognitive test scores, educational achievements and early labor market outcomes of those aged 20-24. From previous studies, we know that these measures explain a substantial portion of the variance across people in employment rates, hourly wage rates, and other outcomes at ages 40-45. By analyzing these skill measures, we can obtain a glimpse of what the prime age earnings of today's youth will be.

In this paper, we compare the distribution of skills in two cohorts.[2] The specific cohorts that we compare are determined by the availability of panel data from the National Longitudinal Survey of Youth, 1997 (NLSY97) for individuals who were aged 12 to 16 in 1997 and from the National Longitudinal Survey of Youth, 1979 (NLSY79) for individuals who were aged 14 to 22 in 1979.[3] We examine the implications of changes in the characteristics of American youth for a set of adult labor market outcomes, focussing on wages and employment. Wages and employment provide natural metrics through which to aggregate

[1]For example, Denison (1974) and Jorgensen et al. (1987) measure how the American labor force changed on the basis of education, work hours, and change in the age and gender mix of the labor force. Using these as inputs in growth accounting, they found that the acquisition of individual skills represents the largest contributing factor to economic growth in the first half of the 20th century. Lange and Topel (2007) find that much of the convergence in earnings across US states between 1940-2000 can be attributed to reductions in skill gaps across states. Other researchers have examined the role of differences in the conditions of skill acquisition to understand economic inequality across and within demographic groups. For example, Juhn, Murphy and Pierce (1991) rely heavily on skill differences between blacks and whites to explain why the decline in the black-white wage gap halted after 1975. They emphasize that the halt in the black-white wage gap reflected how increasing skill prices interacted with pre-existing skill differences between blacks and whites.

[2]Throughout the paper we use the term "skills" to refer to variables that are correlated with labor market outcomes. In the case of race and gender, part of that relationship may be due to discrimination.

[3]In this study we use the word "cohort" to refer to either the NLSY79 or the NSLY97. We use the word "birth-year" to refer to groups of individuals defined by their birth year.

various skill measures into skill indices. We use the wages and employment of members of the NLSY79 cohort during the 1998-2004 survey years.[4]

The first step in our study is to create a set of youth characteristics that correlate with adult outcomes and are comparable across NLSY97 and NLSY79. The second step is to examine the consequences of differences between the characteristics of the 1979 and 1997 cohorts for various adult outcomes. Specifically, we assess what the adult outcomes of the 1997 cohort will be if the relationship between characteristics and adult outcomes turns out to be the same for the 1997 cohort as it has been for 1979. To accomplish this, we draw on the reweighting procedure employed by Dinardo, Fortin, and Lemieux ((1995), hereafter, DFL).[5] Basically, we reweight the 1979 sample to have the same distribution of characteristics as the 1997 sample. We can then compare how outcomes are distributed in the reweighted 1979 sample and in the sample prior to reweighting and can thus measure how the changes in characteristics between 1979 and 1997 affect the outcomes of interest. For example we can estimate how adult wages of the 1979 cohort would have been distributed if the 1979 cohort had the characteristics of the 1997 cohort. Furthermore, we can decompose the difference between this counterfactual and the actual distribution into the contributions of various subsets of characteristics.

The DFL procedure, in contrast to the Blinder-Oaxaca decomposition procedure based on linear regression, does not require one to specify a parametric model relating outcomes to characteristics. It also allows one to examine the impact of changes in particular characteristics on statistics other than the mean. The main disadvantage of the DFL approach is that it does not estimate parameters that relate outcomes to characteristics and that can potentially be interpreted. An alternative approach proposed by Machado and Mata (2005), Melly (2005) and Goesling et al. (2000) explores semi-parametric approaches that restrict the quantiles of the outcome conditional on the characteristics. These approaches strive to partially relax the parametric restrictions imposed by the Blinder-Oaxaca approach, but still provide interpretable parameter estimates. However, the parameters are hard to interpret when the number of conditioning variables is large and interactions among the various characteristics are allowed for. We therefore rely mainly on a DFL type procedure, but also present some results based on the Blinder-Oaxaca regression procedure.

Regardless of method, we require representative samples for both the 1979 and the 1997 cohort that contain characteristics that can be compared across cohorts. Much of the empirical work described below aims to ensure that these conditions are met. We pay particular attention to the AFQT-scores which were administered at different ages and based upon

[4]At this point the respondents to the NLSY79 were 39-47 years old and typically had more than 10 years of experience.

[5]DFL is one of a number of papers in the literature that use propensity scores to re-weight samples. See for example Hirano, Imbens, and Ridder (2003) who show that efficient estimates of average treatment effects of binary treatments on scalar outcomes can be obtained by weighting with the inverse of a nonparametric estimate of the propensity score. This is closely related to the weighing procedure adopted in this paper with the exception that we are relying on parametric estimates of the propensity score. Since we are re-weighting the 1979 cohort to have the characteristics of the 1997 cohort, the "treatment" in our case is giving the 1997 cohort the 1979 wage function.

different test formats. Another crucial issue is whether the 1979 and 1997 cohorts are representative, particularly after attrition and missing data on two key variables are accounted for.

Our main results are as follows.

(1) The 1997 cohort is stronger than the 1979 cohort in most dimensions that matter for wages. In particular, the 1997 cohort is stronger than the 1979 cohort in education, parental education, and test scores. However, the fraction of individuals who lived with both parents at age 14 declined substantially between 1979 and 1997.
(2) The increase in skills of the younger cohort implies an increase in the average wage of about 5% for whites and more for minorities.
(3) The implied differences in employment rates are small overall, but they show increases of .027 for black males and about .025 for Hispanics.
(4) Skill gaps across race and gender decrease. Black and Hispanic males and females gain relative to their white counterparts. White women gain more than white men. The sources of the gains vary across race/gender groups.
(5) The skill distribution widens within race/gender groups as well as for the entire population.
(6) Much of the increase in skills is associated with increases in parental education.

The paper continues in section 2, where we present our methodology. In section 3, we describe the data. We also present evidence on and ways of accounting for biases that may arise due to problems with the NLS97 base year sample, missing data on key variables, and attrition. We present changes in the distribution of skill measures between 1979 and 1997 in section 4. In section 5 we discuss the specifications of the probit models used to adjust the 1979 sample to match the characteristics of 1997. In sections 6, 7 and 8 we present our results. In the final section, we summarize our main findings and outline the next steps in our project

2. ECONOMETRIC METHODS

We now describe our procedure for assessing the changes in the skill distribution across the NLSY79 and NLSY97. We examine various dimensions of skills and these skill measures are typically not reported in a natural metric that allows one to aggregate them into a small set of skill indices. We therefore measure and aggregate the contributions of the various skills using the labor market outcomes (primarily wages) of the NLSY79 cohort during the 1998-2004 survey years. By this time the 1979 cohort had reached the peak of its life-cycle earnings profile.[6]

Our estimates of counterfactual wage distributions answer the question, "What wages will members of the NLSY97 cohort earn at the peak of their life-cycle earnings if they face the same wage distribution conditional on skills that the NLSY79 cohort faced?" Our estimates

[6]Mean wages typically rise rapidly during the first 10 years of experience but do not grow much subsequently. In 1998 the NLSY79 cohort was between 33 and 41 years old, and even the youngest respondents typically had more than 10 years of labor market experience.

also answer the question, "What wages would members of the NLSY79 cohort have earned if they had the observed skills of the NLSY97 cohort?" To answer these equivalent questions, we reweight the NLSY79 to have the same distribution of skills as the 1997 cohort. We then use the reweighted data to generate the counterfactual wage distribution for the NLSY97 cohort.

2.1. **Basic Approach.** For each observation from the NLSY79 we obtain a realization (z, w) of the random vectors Z and W. Observations from the NLSY97 consist of realizations of Z only. We lack realizations of W for NLSY97 and strive to obtain counterfactual distributions of W. Let t and t' stand for the populations that the NLSY79 and NLSY97 are drawn from, respectively.[7] We will sometimes refer to the cohorts by "1979" and "1997" rather than t and t'.

Wages in the economy faced by 1979 are determined by $w = W^{79}(z, u)$, where the vector z is observed and the vector u is not. The function $W^{79}(z, u)$ serves as our metric for aggregating the components of the skill vector z.

Let $g(u|z, t)$ and $g(u|z, t')$ be the conditional densities of u given z for the two cohorts. We make the following key assumption on the relation between observed and unobserved skills:

Assumption A1: *The density of u conditional on z is the same for 1979 and 1997 cohorts:*

$$(A.1) \qquad g(u|z, t) = g(u|z, t') \, .$$

This assumption allows us to construct a counterfactual distribution of wages using $W^{79}(z, u)$ and the observed distribution of Z for the 1997 cohort. Of course, A.1 is not likely to hold exactly. Behavioral responses to differences between t and t' in skill prices, unobserved differences across cohorts in school quality, neighborhood environment, or family environment might lead the assumption to fail. Furthermore, changes in compulsory schooling laws, college tuition subsidies, or race and gender discrimination could alter the relationship between parental education and innate characteristics that are transmitted to children. We cannot directly test (A.1), because u is unobserved. However, in Section 8 we provide indirect evidence based the link from AFQT and education to race, family background and gender. We show that the changes in the observed AFQT distribution are well captured once we account for the changes in the AFQT distribution predicted by race, gender and parental background variables.

Let $f(w|t, z)$ be the density of adult wages of the cohort t (the 1979 cohort) conditional on z. Let $f(w|t', z)$ be the corresponding conditional density for cohort t' (1997) when the wage function is $W^t(z, u)$. Assumption (A.1) implies that the conditional wage density for

[7] The birth years are 1957-1964 for NLSY79 and 1980-1984 for the NSLY97.

cohort t and t' are the same:

$$(2.1)\qquad \begin{aligned} f(w|t,z) &= \frac{d}{dw}\int_{u\in\{u:W^t(u,z)\le w\}} g(u|z,t)du \\ &= \frac{d}{dw}\int_{u\in\{u:W^t(u,z)\le w\}} g(u|z,t')du \\ &= f(w|t',z). \end{aligned}$$

In the remainder of the paper, we suppress the t and t'superscripts on the wage function $W^t(z,u)$ because we always consider the 1979 wage function $W^{79}(z,u)$ rather than the wage function $W^{97}(z,u)$ that the 1997 cohort will face as adults.[8]

Note that $f(w|t)=\int f(w,z|t)dz$. Equation (2.1) implies that

$$(2.2)\qquad f(w|t')=\int f(w,z|t)\psi(z)dz$$

where

$$\psi(z)=\frac{f(z|t')}{f(z|t)}=\frac{p(t'|z)}{p(t|z)}\frac{p(t)}{p(t')}$$

and $p(t'|z)$ and $p(t|z)=1-p(t'|z)$ are the probabilities or "propensity scores" of appearing in sample t' and sample t, respectively, conditional on z.[9] The ratio $\frac{p(t)}{p(t')}$ is the unconditional odds that the observation is from cohort t. Thus the second equality in (2.3) says that $\psi(z)$ is also equal to the product of the odds that an observation comes from cohort t' conditional on z multiplied by $\frac{p(t)}{p(t')}$, the unconditional odds that the observation is from cohort t. The term following the first equality says that the weight function $\psi(z)$ may also be expressed as the relative frequency (density) of the skill vector z in 1997 versus 1979.

Equation (2.2) shows how one obtains the density of adult wages for a population that faces the 1979 wage function but has the observed characteristics of the 1997 sample. To do this, one simply multiplies the density from t by the weight function $\psi(z)$.

We implement (2.2) as follows. First, we use the sampling weights provided by the NLSY79 and NLSY97 to achieve population representative samples.[10] We then pool the data from the two cohorts and estimate the propensity score $p(t'|z)$ using skill measures Z that are observed for both the NLSY79 and the NLSY97 cohort. We then generate the "propensity weights" $\psi(z)$ and apply these weights to the NLSY79 data. The reweighted data are used to generate various statistics of the counterfactual wage distribution $f(w|t')$. In particular, we estimate $f(w|t')$ itself and compare it to $f(w|t)$.

---

[8]If one were to assume a parametric form $W^{79}(z,u)$=$W(z,u;\beta_{79})$ and make assumptions about how β_{97} will relate to β_{79}, then one could use $W(z,u;\beta_{97})$ to forecast the wage distribution for the 97 cohort. We *do not* explore such assumptions and instead simply focus on the counterfactual distribution generated by changing endowments of observed skills between the 1979 and 1997 cohort.

[9]First note that $f(w|t')=\int f(w,z|t')dz=\int f(w|z,t')f(z|t')dz$. Then apply assumption (A.1) to get $f(w|t')=\int f(w|z,t)f(z|t')dz$. Substitute $f(w|z,t)=\frac{f(w,z|t)}{f(z|t)}$ and then use $\frac{f(z|t')}{f(z|t)}*\frac{p(t')}{p(t)}=\frac{f(z,t')}{f(z,t)}=\frac{p(t'|z)}{p(t|z)}*\frac{f(z)}{f(z)}=\frac{p(t'|z)}{p(t|z)}$.

[10]We also generate weights to account for attrition and for non-response for crucial variables. Details are provided in Section 3.

2.2. **Identifying the Contribution of Subsets of Variables to Differences between the 1979 and 1997 Wage Distributions.** Above we showed how to generate the counterfactual distribution of wages implied by a shift in the distribution of the skill vector Z from t to t'. It is natural to ask how much various components of the random vector Z (say Z_1 and Z_2) contribute to the overall change in the distribution of wages from $f(w|t)$ to $f(w|t')$. That is, one would like to decompose the differences between the observed wage distribution of the NLSY79 sample and the counterfactual wage distribution of the NLSY97 sample into variation due to Z_1 or Z_2.

Under Assumption A.1 wages conditional on skill z are identically distributed in t and t′ and therefore

$$f(w|t') - f(w|t) = \int f\left(w|z,t\right) f\left(z|t'\right) dz - \int f\left(w|z,t\right) f\left(z|t\right) dz. \tag{2.3}$$

The change $f(w|t') - f(w|t)$ can be decomposed using a intermediate density $h\left(z\right)$ of the skill vector Z:

$$\begin{aligned} f(w|t') - f(w|t) &= \int f\left(w|z,t\right) f\left(z|t'\right) dz - \int f\left(w|z,t\right) h\left(z\right) dz + \\ &\quad \int f\left(w|z,t\right) h\left(z\right) dz - \int f\left(w|z,t\right) f\left(z|t\right) dz \\ &= \int f\left(w|z,t\right) \left\{\left(f\left(z|t'\right) - h\left(z\right)\right) + \left(h\left(z\right) - f\left(z|t\right)\right)\right\} dz \end{aligned} \tag{2.4}$$

The choice of $h\left(z\right)$ defines the decomposition. From a statistical point of view the choice of $h(z)$ is arbitrary. The merits of any decomposition stem from the economic content of $h\left(z\right)$ which in turn depends on the definitions of the variables Z as well as the particular structure of dependence of components of Z embodied in $h\left(z\right)$.

For the decomposition, we propose to partition the skill vector Z into sub-vectors (Z_1, Z_2) according to the order in which the skill variables are determined. We group higher order variables such as race, gender, and parental background in vector Z_1. These variables are determined prior to lower order variables such as schooling, the AFQT score and the work-transition variables which are collected in the skill vector Z_2.[11] The decomposition $h\left(z_1, z_2\right)$ is then defined as:

$$h\left(z_1, z_2\right) = f\left(z_2|z_1, t\right) f\left(z_1|t'\right) \tag{2.5}$$

From Section 2.1 we know that $f(z|t') = f(z|t)\psi(z)$ where $\psi(z) = \frac{f(z|t')}{f(z|t)} = \frac{p(t'|z)}{p(t|z)}\frac{p(t)}{p(t')}$. We already discussed how to estimate $\psi\left(z\right)$. We can similarly arrive at:

$$h(z_1, z_2) = f(z_2|z_1, t) f(z_1|t') = f(z_2|z_1, t) f\left(z_1|t\right) \psi(z_1)$$

[11] As will become clear shortly, we can decompose the total change $f(z|t') - f(z|t)$ into arbitrarily many sub-vectors and we will ultimately partition the skill vector into variables describing (i) race and gender, (ii) parental background (iii) schooling and cognitive ability and (iv) work transition variables. We argue the variables that appear first in this list are predetermined earlier and are of higher order relative to those appearing later.

where $\psi(z_1) = \frac{f(z_1|t')}{f(z_1|t)} = \frac{p(t'|z_1)}{p(t|z_1)}\frac{p(t)}{p(t')}$. The weights $\psi(z_1)$ are then obtained exactly in the same manner as the weights $\psi(z)$ but using only the variables z_1. Thus, the decomposition defined by substituting (2.5) into (2.4) may be implemented using:

$$\begin{aligned} f(w|t') - f(w|t) &= \int f(w|z_1, z_2, t)\left\{f\left(z_1, z_2|t'\right) - f(z_2|z_1, t)\, f(z_1|t)\, \psi(z_1)\right\} dz \\ &\quad + \int f(w|z_1, z_2, t)\left\{f(z_2|z_1, t)\, f(z_1|t)\, \psi(z_1) - f(z_1, z_2|t)\right\} dz \end{aligned} \tag{2.6}$$

The difference $f(w|t') - f(w|t)$ can be decomposed into changes in as many subvectors $(Z_1, Z_2, ...)$ as desired. For example, if $Z = (Z_1, Z_2, Z_3)$ this is achieved by defining

$$h_1(z_1, z_2, z_3) = f(z_3|z_1, z_2, t)\, f\left(z_1, z_2|t'\right) = f(z_3|z_1, z_2, t)\, f(z_1, z_2|t)\, \psi(z_1, z_2)$$

and

$$h_2(z_1, z_2, z_3) = f(z_3, z_2|z_1, t)\, f(z_1|t)\psi(z_1)\,.$$

Returning to the two-vector case, we obtain the component

$$\int f(w|z_1, z_2, t)\left\{f(z_2|z_1, t)\, \psi(z_1) - f(z_1, z_2|t)\right\} dz$$

of the decomposition (2.6) by first applying $\psi(z_1)$ to the NLSY79 data to get $f(w|z, t)\, f(z_2|z_1, t)$ $f(z_1|t')$ and then subtracting $f(w|t) = f(w|z, t)\ f(z_1, z_2, t)$. This component describes the change in the distribution of w that we would observe if the skill Z_1 was distributed as in period t' but the dependence between Z_2 and Z_1 remained that of time t. For concreteness, assume that Z_1 contains the race and gender identifiers. Then, this component contains the change in w due to the change in the distribution of race and gender in the population between 1979 and 1997. The component is the sum of the direct effect of race and gender on wages and an indirect effect. The indirect effect captures the wage consequences of the effect of race and gender on the distribution of all lower order variables (parental background, schooling, AFQT, and work transition variables). The change in the distribution of the lower order variables that we attribute to the change in race and gender derives from the dependence of the lower order variables on race and gender observed in 1979. We call the second term in (2.6) the marginal effect of the shift in Z_1.

The first term of (2.6),

$$\int f(w|z_1, z_2, t)\left\{f\left(z_1, z_2|t'\right) - f(z_2|z_1, t)\, f(z_1|t)\psi(z_1)\right\} dz\ ,$$

captures the shift in the distribution of lower order variables after already accounting for the shift implied by the change in the distribution of higher order variables (in this example: race and gender). We call the first term in (2.6) the marginal effect of the shift in Z_2.

It should be clear from this discussion that the decomposition depends on the order of (Z_1, Z_2). This is true even if (i) Z_1, Z_2, and U are independent and (ii) $w(u, z_1, z_2)$ is additively separable in u, z_1, z_2 because the conditional density $f(w|z,t)$ is not additively separable in Z_1 and Z_2 even under these conditions.[12]

Because decompositions are not unique, researchers have to take a stand on how Z_1 and Z_2 are causally related. We impose an order on the decomposition that flows from the timing of variables and partition the skill vector into a total of 4 sub-vectors defined by the timing of variables. We start by including race and gender in the prediction model. We then add parental background variables followed by variables capturing individual characteristics such as education and cognitive ability scores. Finally we add variables describing the transition into the work force. Thus, within race/sex categories changing distributions of parental background will entail changes in the resulting individual education and ability distributions. The decomposition therefore implicitly assumes that the cross-sectional relation between family background variables and education and ability in 1979 is causal in the sense that changes in the distribution of parental background result in changes in the individual variables. Similar assumptions are made regarding the relation between parental background, individual education and ability scores and the variables describing the speed with which individuals transition into the workforce.

Below, we will contrast this reweighting decomposition with the more familiar Blinder-Oaxaca regression decompositions common in the literature. The Blinder-Oaxaca decomposition provide easy-to-understand, unique decompositions of the mean that depend on strict linearity and additive separability assumptions. A major advantage of the reweighting decompositions is that we do not need to assume any particular form for the wage function linking skills Z and wages in t. An equally important advantage of the approach proposed here is that the decompositions based on the reweighting method apply to the entire distribution of wages and therefore all statistics of interest. Contrary to the linear decomposition methods, we can for instance describe how the changes in the 25th percentile of the wage distribution decompose into changes attributable to Z_1 and Z_2. We view the sequential decompositions based on the reweighting method and the Blinder-Oaxaca decompositions as complements.

3. Data

The above procedure requires comparable skill measures across surveys. The NLSY79 and NLSY97 surveys are designed for the same purpose: to examine the transition of young Americans into the work-place. Consequently, many variables from these surveys can be compared across the 1979 and 1997 cohorts. Nevertheless, the surveys vary sufficiently to pose challenges to achieving comparability. In this section we describe the samples, consider the representativeness of the NLSY97 base year sample and discuss the effects of attrition and missing data on the AFQT. We also discuss the construction of the wage, AFQT scores, and

[12]The Blinder-Oaxaca decomposition of differences in means is unique even if there is dependence between Z_1 and Z_2 provided that $W(u,z_1,z_2)$ is additively separable in u, z_1 and z_2 and $g(u|z_1,z_1)$ is additively separable in z_1 and z_2. This result only applies to the mean and not to other statistics of $f(w|t)$ and $f(w|t')$.

school to work transition measures. Details of the construction of the samples and of variables are described in Appendix A.

3.1. **Representativeness of the Base Year Samples.** In this section we discuss whether the NLSY97 base year sample is representative and then turn to the problems of attrition and of non-response to the AFQT in Section 3.3.

MaCurdy and Vytlacil (2003) have raised concerns about the representativeness of the NLSY97. In particular, they show that the screening procedures for the NLSY97 found less than two-thirds of the young adults one would have expected to be present based on the 1997 Current Population Survey (CPS). This shortfall in respondents occurred precisely in the age range that the screener interviews sought to identify (12-23), whereas in other ages the expected number of respondents was found. Apparently, families were "hiding" children in the 12-23 age range, perhaps to avoid participating in the survey. MaCurdy and Vytlacil analyze the ETP97, a related sample of 18-23 year olds from the same screening interviews, and find that those responding to the ETP97 are more educated than comparable CPS respondents. They also have more educated mothers.[13] Moore et al's (2000) technical sampling report on NLSY97 also concludes that many parents failed to report children in the NLSY97 age range. However, Moore et al conclude that the distribution of respondents in the screening interviews and the CPS is similar in the dimensions of youth education, parental income and parental education.

We do not fully understand the sources of the differences between the two studies. One difference may arise from the fact that, in the CPS, mother's education is only available for 18-23 year olds who are still living with their mothers. These youths may not be representative of 18-23 year olds as a whole. In this case, MaCurdy and Vytlacil's comparison of the ETP97 to the CPS may not be directly relevant for the NLSY97 sample of 12-16 year olds.

We proceed under the assumption that the available data, after use of survey weights and adjustments for attrition prior to age 22 and for missing data on the AFQT, are representative of the 1997 and 1979 populations, with the obvious caveat that our results will be affected if they are not.

3.2. **Selecting the NLSY79 and NLSY97 Samples.** We use survey years 1979-2004 for the NLSY79 and 1997-2005 for the NLSY97, which were the latest available when we created the data sets for this paper. To maximize sample sizes for minority groups we utilize both the cross-sectional samples and the supplemental samples in the NLSY79 and NLSY97 and use the base year weights provided by the Bureau of Labor Statistics (BLS) to achieve representativeness of the population.[14]

[13] Their comparisons of the PAY80 and PAY97, which are also drawn from the same screening surveys as the NLSY79 and NLSY97 (respectively) show that the fraction of the youths who completed the ASVAB tests and for whom we therefore have an AFQT test score is significantly lower in the PAY97 than in the PAY80. This evidence for PAY80 and PAY97 is consistent with the evidence for NLSY79 and NLSY97 in Table 1.

[14] We do not utilize the panel-weights that are designed to account for (conditionally random) attrition but instead estimate our own weights, as discussed below.

In both surveys we construct our skill measures in a similar manner using the waves up to the survey year when these individuals were 22. We retain the observation that is closest to when the individual was 22 years and 6 months old and then measure variables such as highest grade completed and early work experience by reference to this observation.[15] A total of 9,661 (7,148) individuals should have been observed at age 22 in NLSY79 (NLSY97) and are therefore eligible for our analysis. Appendix Table A itemizes the effects of our sample selection rules on the sample size.

The NLSY97 has a lower retention rate than the NLSY79 at each step of the construction of our sample. In the case of attrition by age 22 this is partly due to the fact that NLSY97 respondents are first interviewed at age 12-16 whereas those in the NLSY79 are first interviewed at age 14-21. Hence, the respondents in the NLSY97 had more time to attrit. In the NLSY97 we lose the largest share of respondents because the AFQT score is missing.[16] If we do not condition on observing the AFQT score, we retain about 85% of the base sample. As a robustness check, we analyze a number of specifications that do not require the AFQT score using both our main sample (the AFQT sample) and a sample that includes those with missing AFQT scores (the full sample).

Table 1 shows how attriters prior to age 22 and stayers differ by observable characteristics. Several of the characteristics are related to attrition. For instance, race correlates with attrition prior to age 22, especially in the 1997 sample. However, the attrition rates are not always negatively associated with characteristics that are favorable for wages. For example, whites are more likely to leave the sample prior to age 22 than are blacks.

The average characteristics of those who remain in the sample to age 22 are very close to the averages for full population represented by NLSY79, in part because we lose only 4.6% of the sample. We also find relatively small differences between the full sample and the stayers in the 1997 cohort in spite of the higher 1997 attrition rate. For instance, the differences between the full population and stayers in the means of mother's education and father's education are only -0.05 and -0.03 years respectively. Nevertheless, we adjust for attrition based on observables using weights obtained from a probit model relating attrition to parental education, parental presence at age 14, indicators by birth-year, urban and SMSA residence status, indicator variables for race and gender, and an interviewer coded variable describing the attitude of the respondent during the interview. For the NLSY97 we also use information on whether the respondent was first interviewed in 1998 rather than 1997.[17]

---

[15] The interviews of a given individual are not exactly one year apart. Consequently, some individuals respond twice at age 22 and some do not respond at age 22 but instead are surveyed twice at age 21 or twice at age 23. We retain the observation that is closest to 22 years and 6 month old and then measure variables such as highest grade completed and early work experience as of this age=22 observation.

[16] Respondents to the NLSY received financial compensation for participating in the ASVAB. The real value of this compensation was significantly higher in 1979 than in 1997, which probably accounts for part of the drop in participation.

[17] A substantial effort was made to locate respondents who could not be found in 1997. Those found were interviewed in early 1998 and were substantially more likely to attrite in subsequent waves.

Non-response to the ASVAB is large enough to potentially result in significant biases, especially in the NLSY97. Table 2 has the same structure as Table 1 and shows how observable characteristics differ depending on whether the AFQT score is missing. The numbers reported in Table 2 account for attrition by age 22 using the weighting procedure described in the previous paragraph. The differences in the mean characteristics by AFQT availability are not uniformly larger in the NLSY97 than NLSY79, but some of the differences between those with or without an AFQT-score are sizable. The difference in racial composition is particularly striking: whites are substantially overrepresented among those with valid AFQT scores. Furthermore, those who have AFQT scores have higher education levels by age 22 and have better educated parents. Overall, those with AFQT scores are more advantaged in both the NLSY79 and the NLSY97.

Fortunately, the difference in characteristics between those with and without the AFQT dramatically overstates the difference in mean characteristics between those with valid scores and the full sample. For instance, those with valid AFQT scores in 1997 have 0.67 years more education by age 22 than those without valid scores but only 0.11 years more education than the full population. We judge these differences to be sizeable, but not forbidding.

We address the problem of attrition and non-response to the AFQT by constructing two alternative sets of weights. The first adjusts only for attrition by age 22 and is used with the "full sample", which does not condition on availability of an AFQT scores. The second set adjusts for both attrition and missing AFQT responses and is used with our main sample, "the AFQT sample". The AFQT sample is the subset of the full sample for whom we have valid AFQT scores. Both sets of weights are estimated using probit specifications based on race, sex, parental presence at age 14, parental education, birth-year indicators, urban and SMSA residence status as well as variables describing the attitude towards the interview. In 1997 we also account for whether the initial interview took take place in 1998 rather than 1997. We estimate these attrition models for the NLSY79 and the NLSY97 separately and apply the weights throughout the analysis as applicable.[18]

It is reassuring that our results for the models outlined in Section 4 that do not require an AFQT score (models 1, 2 and 4) are not sensitive to excluding individuals with missing data on the AFQT score.[19] However, our attrition and AFQT non-response weights do not correct for possible correlation between attrition and unobservables that affect wages or employment conditional on the observable skill indicators in the model.

A final problem arises because 1,383 out of the 9,228 NLSY79 sample members who respond at age 22 do not respond at any time between 1998 and 2004. We use these individuals to estimate the propensity weights, but we cannot use them for generating the counterfactual wage distributions. The results presented below assume that attrition from NLSY79 after age 22 is random. We choose not to construct an additional weight to adjust for this

[18]Since the results in table 2 are generated using the attrition weights, they display the attrition corrected differences across those with and without the AFQT-score among those who do not attrite by age 22.

[19]We cannot perform a similar check for specifications that do make use of the AFQT-score.

because attrition after age 22 in the NLSY79 affects both the actual wage distribution and the counterfactual one. Consequently, it probably has only a second order affect on the difference between the two, which is our main interest.

3.3. **Wages.** Our main metric to measure skills are wages of the NLSY79 cohort in the years 1998-2004. This period spans 4 survey years, since the NLSY79 moved to a biannual format in 1994. We use a regression specification to standardize log real wages between 1998-2004 to the year 2002 and 23 years of potential experience.[20] For each individual we have between 1 and 4 wage observations. We weight each wage observation by the reciprocal of the number of wage observations for an individual. Each individual with at least one valid wage observation receives equal weight in generating the counterfactual wage distributions. This implies that our wage statistics reflect the wage distribution of the population "while working".[21] There is no need to reweight the statistics for employment rates, because employment status is observed for each valid interview.

3.4. **Comparability of the Paper and Pencil (P&P) and Computer Assisted Test (CAT) of the ASVAB.** Our measure of cognitive ability, the AFQT-score, is a composite score derived from the ASVAB. For the NLSY79 the test was administered in 1981 when respondents were between 16-21 years old, whereas for the NLSY97 the test was administered at the beginning, when individuals were between 12-16 years old. We exploit the overlap in the test-taking age across both cohorts by applying an equipercentile procedure on each cohort with the population of test takers who were 16 year olds when taking the test.

We must also account for the fact that the test-format differed between surveys. The NLSY79 cohort was administered a pencil and paper (P&P) version of the ASVAB while the NLSY97 took a computer assisted test (CAT) format. To achieve comparability between the two test formats we rely on a mapping between the P&P and the CAT test format.[22]

In Appendix A, we examine whether the equipercentile matching of scores across ages is valid. When we match percentiles across ages we implicitly assume that an individual's rank within the age distribution summarizes all relevant information about individuals' skills contained in the AFQT score. Consequently, individual characteristics should contain no differential information about individual scores by age after matching individuals across percentile ranks. To test this hypothesis, we regress the test-scores on personal characteristics

[20]For this purpose we estimate a log wage equation separately for high school drop-outs, high school graduates and individuals with more than a high school degree. We include a quartic in experience and year-effects.

[21]If we did not weigh person/year observations in this manner, then the statistics would be representative of those who are working at a point in time. Consequently, they would give more weight to those for whom we observed a valid wage more frequently. We do not use time averages for each individual because in the presence of transitory wage variation, the distribution of the time averages depends on the distribution of the number of observations per person.

[22]The mapping was constructed using test results from a sample of individuals who were randomly assigned to take either P&P or the CAT test. (See Segall 1997) The mapping assigns scores to equalize percentiles on the various subtests of the P&P and the CAT. By definition this amounts to transforming the P&P subtest scores with a monotone function that matches the distributions of the CAT scores. We thank Daniel Segall for providing us with the P&P equivalents of the CAT scores for the NLSY97 sample.

measured at age 22 as well as the interactions of these characteristics with the age at which the ASVAB was taken. For both surveys, we find that the coefficients of the regression of age-adjusted test scores on individual characteristics do not vary with test-taking age. (See Appendix Table B) This suggests that the relation between AFQT scores and race, parental education, and individual education at age 22 is the same across test taking ages. Appendix Table B says little about the quality of the mapping from the P&P to the CAT version of the test, which is considered in Segall (1997).

3.5. **School to Work Transition Variables.** We construct the vector *SCH_WORK* of variables that measure whether an individual's schooling career was continuous and whether the individual had a smooth transition into the working population. We define $workuniv$ to be 1 if an individual has not attended school for at least 2 years prior to age 22 and 0 otherwise. The variables $early$, $ontime$, and $late$ are indicator variables generated by comparing school leaving age for these individuals with age+6+highest grade completed. The variable $work$ indicates whether individuals have worked for at least 14 weeks in one of the first two years after leaving school. The four *SCH_WORK* variables are set to 0 for individuals who attended school at least once between ages 20-22 ($workuniv = 0$).

4. Characteristics of the 1979 and 1997 Cohorts

Table 3 presents summary statistics for the key skill indicators used in this study. These statistics are supposed to describe the population in 1979 and 1997 and are therefore computed using the NLSY cross-sectional weights adjusted for attrition by age 22 and AFQT non-response.

Most characteristics show improvement between the NLSY79 and NLSY97. The mean of AFQT rises from 42.35 to 44.19 and highest grade completed as of age 22 increases from 12.64 to 13.02.[23] Average education of both mothers and fathers increased substantially over this time-period. For example, mother's education rose from 11.77 to 12.71 – an increase of about 11 months.

While there are gains in most skill characteristics, the dramatic decline in the percentage of children who grow up in traditional family settings is an important exception. The percentage of individuals living with both biological parents at age 14 drops from 75.23% in 1979 to only about 52.98% in 1997. This decline is mostly accounted for by an increase in the number of children growing up without their biological father. By 1997, 41.08% of children are not living with their biological father. We were sufficiently surprised by the very large fraction of individuals living outside of traditional family structures that we confirm this result using Census data in Appendix B.

[23]Large secular increases in IQ scores have been demonstrated in all countries for which data on IQ scores is available over time. This "Flynn"-effect (see Flynn (2000)) is so large as to cast doubt on the comparability of IQ scores over time. The AFQT-test is strictly speaking not an IQ test and it is not clear whether it is subject to the same concern. The increase in AFQT-scores between the 79 and 97 cohorts of about 1/10th of a standard deviation does not strike us as implausible a priori. Nevertheless, caution is necessary when comparing ability test scores across temporal and cultural distances.

Panel B of Table 3 summarizes the main characteristics separately for whites, blacks, and Hispanics. The changes for the subgroups generally parallel those for the sample as a whole. However, the increase in AFQT scores is substantially larger for blacks and Hispanics than for whites. HGC rose by 0.83 for Hispanics, 0.30 for blacks, and 0.45 for whites. All races have substantially better educated parents in 1997, reflecting secular gains in education over the last 50 years. These gains are larger for minorities.

The decline of the traditional family structure is dramatic for whites and blacks and large for Hispanics as well. Across the two cohorts, the percentage of youths living with both biological parents at age 14 fell by 21.99 for whites, 24.87 for blacks and 9.49 for Hispanics. Among the 1979 cohort, only a slim majority (50.21%) of black youths lived with both parents. Continued decline in parental presence results in the striking fact that only about 1 in 4 black youths in the 1997 cohort grew up in a household with both biological parents present. The decline of traditional family structures has been slower among Hispanics and the 1997 distributions of white and Hispanic youths across family types are comparable.

Table 4 reports results for AFQT, education, and the school to work transition variables by race and gender. (The parental education and family structure measures are omitted to save space.) Females gained relative to males in all groups. In 1979 white males and females are about equal in average education and AFQT scores. Both groups show improvement, but by 1997 white females exceed males in both of these skill dimensions and have an education advantage of one half year. Hispanic females and black females gain relative to their male counterparts, particularly black females. Black females had very large gains in AFQT scores (8.45 points) and also gained about 0.45 years in highest grade completed. Black males gained 5.6 points on the AFQT but only 0.17 years of education. Black males also had the smallest increase in the enrollment rate at age 22.

In both cohorts, blacks and Hispanics are disadvantaged relative to whites. The gaps decreased along some but not all skill dimensions between 1979 and 1997. For example, mean AFQT scores rose by 1.48 points for white, 5.6 for black, and 4.88 for Hispanic males. By 1997 Hispanic females had closed the HGC gap with black females and Hispanic males had surpassed black males. However, the share of individuals who make a seamless transition between schooling and work rose faster for white males than for their black and Hispanic counterparts. On the other hand, white females stagnated along this dimension, while black and Hispanic females experienced substantial gains.

Although the results show increases in education for most measures across all race and demographic groups, the increases are not uniform across the distribution of schooling. Rather, we observe that among whites and blacks the share of individuals with HS diplomas stayed roughly constant, while the fraction of those with more than 14 years of education by age 22 and the share still enrolled at age 22 increased substantially for both groups. These facts indicate that the conditional probability of continuing with school once a high school diploma has been obtained increased substantially across the two cohorts. In the case of Hispanics, the high school graduation rate rose by 10 percent, and the increase in education is more uniform. The education statistics presented in Table 4 suggest that at the top of the education distribution there has been a significant response to the increases in the returns to education observed throughout the 1980s and 1990s, although our results below indicate that much of the gain reflects the increase in parental education rather than a behavioral response. At the same time, however, there is a persistent fraction of the population that still does not acquire a high school degree.[24]

5. Estimation of Propensity Scores

We now turn to the estimation of the propensity score conditional on our available skill measures. Equation (2.3) shows the relation of the propensity weights to the estimated propensity scores. We estimate the propensity score using probit specifications based on the various sets of skill measures. We use flexible functional forms for the latent index of the probit model so as not to restrict the changes in the skill distributions across cohorts unduly.

We consider various specifications for the skill vector Z. We organize the skill variables into a hierarchical structure according to the degree of predetermination. Our most basic skill vector consists of variables that are outside the individual's control: race and gender (Model 1). We then sequentially add additional variables related to individuals skills. *Each set of additional variables is fully interacted with race and gender.* In Model 2 we add parental education and indicators for presence of mother and father at age 14 (*parents)* as measures that influence skill development and economic decision-making across generations, but are predetermined relative to the skill characteristics that refer to the individual herself. Since changing social norms regarding childbearing out of wedlock may alter the relationship between the parental presence indicators and unobserved characteristics of family background, we experiment with excluding the parental presence indicators. In Model 3 we add a quadratic in the AFQT score. If cognitive skills are fully determined by inherited factors, environmental factors and primary schooling and are not amenable to individual investments after the early teens, then AFQT will be predetermined relative to variables referring to educational attainment and the transition to work. In Model 5 we add education, as measured by a vector of dummy variables for highest grade completed at age 22 (*HGC*) as well as indicator variables for whether individuals are enrolled at age 22. To the extent that cognitive tests scores are influenced by high school and college education, as suggested by a number of studies, one might want to reverse the order of AFQT and education.[25] Model 4 drops the AFQT terms and keeps the education terms. For the most part, our results are robust to switching the order of or including AFQT and schooling at the same time. Our full model (model 6), adds the

[24]Our results regarding high school graduation rates for the two cohorts are broadly consistent with those of Heckman and Lafontaine (2007). They show using multiple data sources that high school graduation rates have stagnated over the last 20 years, while we show a small increase for the specific years of the NLSY79 and 97. Both studies show an increase in college attendance conditional on high school graduation for the birth cohorts covered by the NLSY79 and NLSY97.

[25]See Neal and Johnson (1996), Korenman and Winship (2000), Hansen, Heckman, and Mullen (2004), and Cascio and Lewis (2006).

components of the vector SCH_WORK to model 5. We conjecture that spending time neither at work nor at school is a negative indicator for future employment and wage rates.

Equation (5.1) below presents the exact specification of the latent index for Model 6, which nests the other models. Denote the latent index determining whether an individual is observed in the NLSY97 rather than the NLSY79 as θ_i. The first line contains race and gender (Model 1). The second line adds the variables $MHGC_{e,i}$ and $FHGC_{e,i}$, which are dummy variables indicating whether the highest grade completed by mother and by the father is e. Missing data on parental education are treated as a category and observations with missing parental education are included in the analysis. The third line adds family structure indicators. Lines 1, 2 and 3 constitute Model 2. Line 4 adds interactions of a quadratic in the AFQT with race and sex (Model 3). Line 5 adds the HGC and $enroll$ (Model 5). To obtain Model 6, we add lines 6 and 7, which contain the variables describing the transition from schooling to work.

$$
\begin{aligned}
(5.1)\quad \theta_i \quad = \quad & \sum_{s,r} Sex_{s,i} Race_{r,i} \beta_{s,r} \\
& + \sum_{s,r} Sex_{s,i} Race_{r,i} (\sum_{e} FHGC_{e,i}\beta_{fe,s,r} + MHGC_{e,i}\beta_{me,s,r}) \\
+ \quad & \sum_{s,r} Sex_{s,i} Race_{r,i} (\mathit{Mom\_only}\beta_{mo,s,r} + \mathit{Dad\_only}\beta_{fo,s,r} + \mathit{Mom\_Dad})\beta_{fm,s,r}) \\
& + \sum_{s,r} Sex_{s,i} Race_{r,i} (afqt_i \beta_{1afqt,s,r} + afqt^2 \beta_{2afqt,s,r}) \\
& + \sum_{s,r} Sex_{s,i} Race_{r,i} (HGC_i \beta_{hgc,s,r} + enroll_i \beta_{enr,s,r}) \\
& + workuniv_i * \sum_{s,r} Sex_{s,i} Race_{r,i} (early_i \beta_{ear,s,r} + ontime_i \beta_{ot,s,} \\
+ \quad & workuniv_i * \sum_{s,r} Sex_{s,i} Race_{r,i} (late_i \beta_{lt,s,r} + work_i \beta_{w,s,r}) \\
& + \epsilon_i
\end{aligned}
$$

The error ε_i in the latent index function is assumed to be normal. We estimate the models by MLE-Probit after pooling the NLSY79 and NLSY97 samples. The base year sample weights provided in NLSY are used in the estimation. As discussed in Appendix A, we adjusted these weights by the age of immigration for individuals not born in the US to account for the differences in scope between NLSY79 and NLSY97. When we use the full sample of individuals who are observed at age 22, we adjust the base year sample weights for both cohorts for attrition prior to age 22 based on cohort specific probit models relating attrition to the observable characteristics that appear in the specifications of θ_i for the full sample. When we use the AFQT sample, we estimate a probit model for the joint probability of attrition prior age 22 and AFQT non-response using the same variables. These sample and attrition weights are omitted from the presentation to keep the notation simpler.[26]

6. Changes in the Skill Distribution between NLSY79 and NLSY97

In this section we present the overall changes in the skill distribution across cohorts using labor market outcomes in middle ages measured using the methodology and data presented in Section 2-4.

6.1. **Overall increase in skills.**

The first result to note is that the 1997 cohort is more skilled than is the 1979. Table 5 and 6 show how employment and log wages are predicted to change due to the variation in skill endowments across the two cohorts. Columns 1 and 2 present the results for the observed outcomes in the 1979 cohorts. The remaining columns present the difference between counterfactual statistics and the actual 1979 values. Our main results are in column 3, where we match on the full set of variables including parental education, parental presence, schooling, the AFQT, work transition, and race and gender (Model 6). Columns 4 and 5 report results for the specification without the work transition variables and without the AFQT score (Model 4) estimated using the AFQT sample and the full sample respectively. Column 6 omits the work transition variables from the full specification. We report bootstrapped standard errors in parentheses.[27]

Using the metric of employment rates we find little difference across cohorts. For men and women combined, the shift in skill components would lead to a decrease in the employment rate of about 0.001 when we use the full set of skill indicators (model 6, bottom row, col. 3). This is the net result of an increase of 0.005 for males and a decrease of 0.007 for women. We find more substantial increases for black men and for Hispanic men and

[26] We have explored even more flexible functional forms for the propensity models than Model 6. When we use more flexible functional forms we obtain some extreme values for the propensity weights. This is especially true for the minority groups since all specifications are fully interacted by race and gender. Appendix Table D shows the distribution of the propensity weights obtained for various models. By construction the propensity weights average to 1. Consider Model 6. The 1st percentile value of the weight is essentially 0, whereas the 99th percentile in the wage distribution has a weight of about 7. This indicates that the combination of characteristics associated with the 99th percentile in the weight distribution is about 7 times as likely in the 1997 as compared to the 1979 cohort. If we go even further into the tail, then we observe some extreme weights. For example, one individual, (a black female with 16 years of education and an AFQT score of 87 who was enrolled in school at age 22 and did not live with either biological parent at 14) has a propensity weight of 88. There are 37 individuals with weights above 10 and 8 with weights above 20. These high propensity weights are disproportionately found among Hispanics. (Seven out of 8 with a weight larger than 20 and 23 out of 37 with a weight greater than 10 are Hispanics.) Much of this is generated by the quadratic interaction in the AFQT-score with race and gender, which lead to extreme propensity weights for individuals in the regions of the support of the AFQT that are thinly populated by their race and gender group. To limit the influence of observations with extreme weights, we cap the propensity weights at 10. Capping the highest propensity weights tends to lower the estimates of gains at the very top of the minority distributions. Once we cap, our results are typically not sensitive to varying the model specifications, the value of the cap or the weighting procedures to account for attrition and non-response.

[27] We choose bootstrap samples by selecting individuals with replacement from subsamples stratified by race and ethnicity and gender so as to preserve the basic demographic composition of the samples. Each replication sample consists of a bootstrap sample stratified along sex and race from the NLSY 79 and NLSY 97. We then applied all of our procedures including the estimation of *weights for attrition and AFQT-nonresponse* to the replication sample. We repeated this process 300 times.

women, particularly when we use the full set of skill indicators. For example, the shift in skill components for black men implies an increase of .027 in the employment rate, from .854 to .870. The employment results by race and gender are somewhat sensitive to the specification, but the findings for the full population and for males and females separately are robust to the choice of specification.

Using the metric of wages we find that the 1997 cohort is stronger than the 1979 cohort. The bottom row of Table 6 shows that on average skills increased between 1979 and 1997 by about 6-7%, regardless of whether we use the full model (column 3), exclude the AFQT and work transition variables from the model (column 4) or include persons with missing AFQT scores (column 5).

6.2. **The Effects of Skill Shifts over the Wage Distribution.** Table 6 and Figure 1 show the shift in skills across the wage distribution.[28] The shift implies a wage increase of only about 2-3% below the 10th percentile. Between the 20th and 85th percentile there is a large region with gains of about 5-6% while gains are in the 10% range in the top decile. The increase at the top of the distribution and the smaller increase at the bottom imply a widening in the skill distribution. This will, all else equal, result in increased economic inequality over the next decades.

Figure 1 also shows the gains across the log wage distribution for various specifications. One can see that the changing racial composition of the work-force generates only a small, fairly uniform decline in our skill metric. Adding parental education and presence indicators (model 2) implies a shift in the log wage of about 5% over most of its distribution. The additional gain from adding all other components (model 6) is typically between 1 to 2 percent. The results with only AFQT and HGC (model 5) are similar to the results with AFQT, HGC, and the school to work transition variables (model 6). Thus, we find an increase of about 7 percent in skills between the 1979 and 1997 cohorts, about 5 percent of which is associated with shifts in parent background. It is important to remember that the shift attributed to parental background includes the effects of induced changes in schooling and AFQT scores holding the conditional distribution of schooling and AFQT constant. Nevertheless, the results here indicate that more than two thirds of the shift in skills between 1979 and 1997 is linked to parental education. Another way of putting this is that conditional on parental education and family structure, other skill measures have only gained by small amounts.
We discuss the contributions of the various skill components in more detail in Section 7.

6.3. **Race and Gender Gaps.** Overall we find a modest widening in the skill distribution for the recent generation. At the same time we find gains in skill endowments for various groups that were significantly disadvantaged in the 1979 cohort.

---

[28]We present results from the 5th to the 95th percentiles. Results from the tails are consistent with our findings here, but noisy. The text figures focus on the difference between the actual 1979 distribution and the counterfactual distribution. Appendix Figure A-1 presents the actual wage density in 1979 and the counterfactual density based on model 6.

The two panels of figure 2 present the expected changes in the log wage distribution conditional on race and gender along with 1.65 standard error bands. The counterfactual distribution is obtained by reweighting to match the changing distributions of all our skill measures (parental education, parental presence, schooling, AFQT, and work transition). The y-axis within each panel is on the same scale and thus results across race can easily be compared. The scale differs across gender, however.

For males we find that blacks and Hispanics gain significantly relative to whites over most of the wage distribution. Only at the very top are gains of white males similar to those of their black and Hispanic counterparts. The shift in characteristics implies a reduction in the mean log wage gap between white and black men from 32.2% to 28.2% and a reduction at the 90th percentiles for the two groups from 36.7% to 32.4%. Only above the 90th percentile does the gap fail to narrow, as indicated by Figure 2, panel 1. The corresponding reductions in the gap between white and Hispanic men are from 18.2% to 14.3% at the mean and from 18.94% to 15.6% at the 90th percentile The results in the upper tail are somewhat sensitive to the specification of the propensity weight model.

We find significant widening in skills within both the black and Hispanic male population. And, as already described, on average the skills of black and Hispanic males increase relative to whites. Based on these findings we expect a significant proportion of the black and Hispanic populations to enter the middle class. In the NLSY79 a black male at the 75th percentile of the black male wage distribution is at the 47th percentile of the overall distribution of males. A Hispanic male at the 75th percentile of the Hispanic male distribution is at the 67th percentile of the overall distribution. The counterfactual wage distributions using the full set of characteristics imply that in 1997 a black male at the 75th percentile would lie at the 60th percentile of the counterfactual distribution for all males and that a Hispanic male at the 75th percentile would find himself at the 72nd percentile.

Figure 2.2 suggests that the wage gains of females are likely to exceed gains among males. Again, Hispanics show the most dramatic gains. Over the entire distribution females are expected to gain between 10 and 20%. Likewise, black females are expected to gain over the entire distribution, with gains greater than 10% for about two-thirds of the distribution. Gains for white women are small near the bottom of the distribution but increase along the entire distribution. Above the 80th percentile the implied gains exceed 10 percent. The results imply that changes in skill components will reduce the average gap in the wages of men and women from 27.82% to 26%. The male/female gap in the 10th, 50th, and 90th quantiles will decline by 1.5%, 4.2%, and 1.3% respectively. The narrowing gender gap reflects a larger increase for women than men in education and a somewhat larger increase in AFQT.

Overall we find that if the conditional distribution of adult wages for the 1997 cohort turns out to be similar to that of the 1979 cohort, then an increase in the skill endowments of blacks and Hispanics relative to whites and of women relative to men will contribute to a decline in economic inequality across groups as the 1997 cohort enters its prime. However, substantial group differences in wages will persist unless wage gaps conditional on skill characteristics decline. We also find that the changing distribution of skills will lead to more inequality within demographic subpopulations.

7. Identifying the Contribution of Subsets of Variables to Differences between the 1979 and 1997 Wage Distributions

In this section, we examine in more detail how much the different skill components contribute to the overall changes in skills between 1979 and 1997.[29] First, we present decompositions based on sequential applications of (2.6) and report the marginal effects of each additional group of variables across the entire counterfactual wage distribution. Below, we will compare these decompositions with decompositions of the mean obtained using regression based approaches.

Table 7 breaks up the difference between the actual wage distribution for 1979 and the counterfactual distribution obtained as we sequentially add variables to the skill vector Z. The first column shows the actual distribution of the NLSY79 wages and is the same as Table 6, column 1. The second column shows the marginal effect of the shift in race and gender on the mean and various percentiles of the wage distribution. As we have already noted, these shifts have a small negative effect. One should keep in mind that the marginal effect in column 2 is the sum of the direct effect of race and sex on wages and the indirect effect that arises because race and sex are associated with other characteristics, such as AFQT and parental education. Column 3 reports the marginal effect of adding parental education and presence indicators. (The combined effect of race and sex and the parent variables may be calculated by summing columns 2 and 3.) The parent variables are quite important. They imply an increase in the mean wage of about .055 log points. Column 4 reports the marginal effect of adding AFQT. The marginal shift in the AFQT distribution implies only a small additional increase of 0.002 across the entire distribution. In column 5 we add HGC. Adding schooling has a fairly sizable effect of 0.018 log points at the mean and 0.002, 0.024, and 0.02 at the 10th, 50th, and 90th quantiles respectively. In column 6 we add the school to work transition variables. These variables have a small negative marginal effect on the counterfactual wage distribution. This indicates that given the observed changes in other skill characteristics we would have expected larger gains in the work transition variable than we actually observe in the 1997 data.[30]

[29] All calculations in this section are based on the AFQT sample.

[30] Appendix Figure A-2 provides a different take on the shifts in various skill indicators. Each data-point in the figure refers to individuals in a percentile of the log wage distribution in 1979. The vertical axis displays the weight of these individuals in the sample after reweighing the 1979 data to match the 1997 distribution. We smooth the information in figure A-2 using a non-parametric kernel regression. The figure shows that matching the 1979 cohort to the 1997 distribution of parental education and parental presence means increasing the weights for those in the top half of the distribution at the expense of those in the bottom part. Accounting for schooling and AFQT scores leads to a further increase in the weights on NLSY79 cohort members who had characteristics that place them in the upper range of the wage distribution.

Table 8 breaks down the marginal effects for each race/sex group. The results show much larger effects of parental background for Hispanics than for whites and blacks, as we discuss in more detail below.

As we discussed in Section 2.2, the marginal effects of particular variables depend on the order in which they are introduced. There is a reasonable case for introducing race and sex followed by parental background before adding AFQT or education outcomes. But the AFQT and school outcomes are jointly determined, so it is far from obvious that causal priority should be given to AFQT. In column (7) and (8) of Table 7 we switch the order in which we introduce AFQT and HGC. Reversing the order does not change the finding that the change in schooling has a relatively large marginal effect on the wage distribution while adding the AFQT has only a small marginal effect. Indeed, from Table 7, column 8 we can see that once schooling has been accounted for, the marginal effect of the AFQT is negative at the mean. This pattern holds among white males and females and Hispanic males. On the other hand, for black males the improvement in AFQT seems to be as or more important than the increase in HGC. For black and Hispanic females the joint increase in schooling and AFQT is important, but we cannot determine the relative contribution, as it depends on the order of inclusion in the propensity model.

7.1. **Regression decompositions.** In this section we provide regression decompositions of the mean and compare them to the DFL based decompositions. These comparisons give insights into the role of non-linearity and dependencies among the variables in generating the overall shift in wages. We find that nonlinearities in the wage function, which include non-linear effects of particular variables and non-separability among the variables are only moderately important. In contrast, dependencies among the skill variables have large impacts on how the overall change in skills is decomposed among variables. In particular, parental education not only has a substantial direct impact on the change in mean log wages, but also a large indirect impact through other variables.

To set the stage for the regression decompositions and establish how they relate to the DFL decomposition into marginal effects, we need some assumptions in addition to (A.1). They are

(A.2) $W(u, z_1, z_2, .., z_K)$ is additively separable in z_1, z_2, z_K and the function $\varepsilon(u)$,

(A.3) $W(u, z_1, z_2, .., z_K)$ is linear in z with slope coefficients

(A.4) $E(\varepsilon(u)|z_1, z_2, .., z_K)$ is additively separable and linear in z_1, z_2,.z_K

and

(A.5) $E(Z_k|z_1, .., z_{k-1}, t) = \pi^t_{k0} + z_1\pi^t_{k1} + z_2\pi^t_{k2} + ... + z_{k-1}\pi^t_{kk-1}$ where $\pi^t_{kk'}$ are coefficient matrices conformable to z_k and $z_{k'}$.

Assumptions A.1-A.4 imply

$$E(W|z, t) = \beta_0 + z_1\beta_1 + z_2\beta_2+, .., z_K\beta_K.$$

Traditional regression decompositions report partial effects of shifts in the mean of particular variables holding the mean of all other variables constant. The "partial effect" of the shift in the mean of Z_k is $[E(Z_k|t') - E(Z_k|t)]\beta_k$. We estimate the β's by OLS. Of course, β_k is the partial effect of the shifts with u held constant only if $E(\varepsilon(u)|z) = 0$. As we have already noted in section 2.2, the partial effects are well defined without specifying a counterfactual for the other Z variables only if the additive separability assumptions hold.[31]

One can also use linear regression to estimate marginal effects which account for dependencies among the variables in a manner analogous to the DFL decompositions. Define $\tilde{Z}_k = Z_k - (\pi^t_{k0} + Z_1\pi^t_{k1} + Z_2\pi^t_{k2} + ... + Z_{k-1}\pi^t_{kk-1})$ for $k > 1$. One may rewrite $E(Z_k|z_1, .., z_{k-1}, t)$ as $(\gamma^t_{k,0} + z_1\gamma^t_{k1} + \tilde{z}_2\gamma^t_{k2} + ... + \tilde{z}_{k-1}\gamma^t_{kk-1})$, where γ^t_{kj} is a function of the $\pi^t_{k',k''}$, $k \geq k' > j$; $k \geq k'' \geq j$.[32]

Under assumptions A.1 plus A.2-A.5, the marginal effect of Z_1 may be written as

$$[E(Z_1|t') - E(Z_1|t)]\beta_1 + \sum_{\ell=2}^{K}[E(Z_1|t') - E(Z_1|t)]\gamma^t_{\ell,1}\beta_\ell.$$

The first term is the partial effect of Z_1. The second term is the indirect effect operating through Z_2 through Z_K. One may write the marginal effect of Z_k as

$$[E(\tilde{Z}_k|t') - E(\tilde{Z}_k|t)]\beta_k + \sum_{\ell=k+1}^{K}[E(\tilde{Z}_k|t') - E(\tilde{Z}_k|t)]\gamma^t_{\ell,k}\beta_\ell.$$

For each $\ell > k$ we estimate the γ^t_{lk} by regressing Z_ℓ on the higher order variables $[Z_1, \tilde{Z}_2.., \tilde{Z}_{\ell-1}]$ using the 1979 sample.

Below we present three different estimates of the effects of a variable on the means. The first is the marginal effect based on the DFL decomposition and the second is the marginal effect based on the regression decomposition. These are alternative estimates of the same parameter if A.2-A.5 hold. We also estimate the partial effect from the regression decomposition. Comparing the marginal effects of the DFL and the regression decomposition informs us about the role of non-linearity and nonseparability in the wage function. Comparing the partial effect and the marginal effect of the regression decompositions informs us about the role of dependencies between variables.

Table 9 displays the three effects for the full population using the same order as Table 7. The OLS coefficients on race, sex, father's education, mother's education, HGC, AFQT, and the school to work transition dummies are in column 1. For ease of interpretation, the education variables and AFQT enter in linear form. The second column reports the difference between the 1997 and 1979 cohorts in the means of each of the characteristics. The third column reports the implied partial effect of shifts in variables in each grouping. It is based

[31] In contrast to additive separability, linearity in each Z is not crucial. We use a linear specification for *HGC, father's HGC, mother's HGC* and *AFQT* to make the regression results easier to present and interpret.

[32] For example, $\gamma^t_{kk-1} = \pi^t_{kk-1}$ and $\gamma^t_{kk-2} = \pi^t_{k,k-2} + \pi^t_{k-1,k-2}\pi^t_{k,k-1}$. γ^t_{kk-j} is determined by the recursive formula $\gamma^t_{kk-j} = \pi^t_{kk-j} + \sum_{i=1}^{j-1}\pi^t_{k-i,k-j}\gamma^t_{k,k-i}$. We construct $\tilde{z}_2.,,,\tilde{z}_{k-1}$ and directly estimate the γ^t's.

on the coefficients in column 1 and the mean shifts in column 2. The fourth column reports the marginal effect of each additional set of variables, which is the sum of the partial effect in column 3 and the indirect effect of the variable on the means of the variables in the corresponding rows of the table weighted by the multiple regression coefficients from column 1. The order in which groups of variables are added is the same as the order of the rows. The order corresponds to Table 7, although we provide a more detailed breakdown of marginal effects in the regression case. In column 5 we display the corresponding DFL estimates of the marginal effects, aggregating over parental background variables.

For the full population, the marginal effects from the regression decomposition do differ from those obtained from the DFL procedure. Overall, the regression decomposition implies a mean log wage increase of 0.04, which is somewhat smaller than the estimate of 0.058 that we obtain using the DFL approach. For individual variables, we find some modest differences between the marginal effects from the regression decomposition in column 4 and the marginal effects from the DFL procedure that are found in column 5. Nonlinearities and nonseparability among the various skill components matter, and it is not sufficient to simply decompose the means with a simple additively separable linear regression to get an accurate description of the variation in skills between 1979 and 1997.

When we compare the partial and marginal effects in columns 3 and 4 we see how important the dependence among variables is for determining how much a variable contributes to the overall increase in skills. This is particularly true for parental education and family structure. The partial effect of the increase in parental education is 0.019. On the other hand, the shift away from 2 parent families implies a reduction of 0.008. These estimated partial effects hold constant HGC, AFQT, and the school to work transition as family background varies. Combining these estimates implies that the partial effect of the shift in parental background is 0.011. The marginal effects of the family background variables are much larger than the partial effects. These marginal effects include an indirect effect operating through HGC, AFQT and school-to-work transition. Both the DFL and the regression based estimates in table 9 indicate that the marginal effect of the changes in parental background variables is to increase skills by about 5-6%. For the regression decomposition, the marginal effect of HGC, AFQT, and school-to-work combine to -0.002 (DFL: 0.012) which is much smaller than the sum of the partial effects, which is 0.022. The partial effects are small because we observe only modest increases in skills once we account for parental education. The shift in parental background induces a large part of the increase in individual skill measures such as schooling and the AFQT.

The relative contributions of HGC and AFQT to total skills are also interesting. The means of both HGC and AFQT increase between 1979 and 1997. If we value these increases using the positive regression coefficients (Table 9, col.1), then we observe partial effects of HGC and of the AFQT equal to 0.017 and 0.012 respectively. In contrast, the marginal effect of the shift in HGC (with AFQT excluded) is 0.017 and once HGC is included, the marginal contribution of AFQT is negative (-0.008). The regression estimates of the partial and marginal effects of HGC and AFQT are consistent with the pattern of marginal effects found with DFL. The negative marginal effect of AFQT when HGC is already included stems from the fact that based on the shifts in race and gender, parental background and schooling we would expect the AFQT score to increase by about 4 points, while the actual increase is only 2.4 points.

Table 10, panels A and B present the regression decompositions separately by race and gender. As for the aggregate population, we find that the marginal effects of parental education are strikingly large and consistently exceed the partial effects. For minority males, the marginal effects of parental education are as large as the total increase in skills. For white males and females the marginal effects of parental education actually exceed the total measured increase in skills. This implies that for white males and females, skills as measured by parental presence, HGC, AFQT, and work-transition declined after accounting for the direct and indirect effects of changes in parental education. For white males the total increase in log wages is 0.028, while the marginal effect of parental education suggests an increase of 0.072. The difference is mainly due to the decline in the number of 14 year olds living with their parents and the decline in the work-transition variables, while HGC and AFQT together contribute a negligible amount (-0.003) even though both variables have substantial positive regression coefficients and partial effects. The DFL estimate is -0.004. The combined marginal effects of HGC and AFQT are positive but relatively small for black and Hispanic males—0.012 and 0.008 respectively. The partial effects of both variables are larger.

The regression estimates of marginal effects indicate that the only demographic groups that experience an increase in skills conditional on parental education are black and Hispanic females. For black and Hispanic females the observed marginal effects of parental education are as large as those observed for whites of both gender and for minority males. However, black and Hispanic females have also made large gains in HGC and AFQT conditional on family background. The combined marginal effect of HGC and AFQT is 0.055 for black females and 0.06 for Hispanic females, which are about as large as the marginal effects of parental education. The partial effects of HGC and AFQT are larger than the corresponding values for black and Hispanic males.

Note also that blacks (both males and females) differ from whites and Hispanics in the relative marginal effects of HGC and AFQT. Both the regression estimates and the DFL estimates indicate that for whites and Hispanics of both genders the marginal effect of AFQT is much smaller than the marginal effect of HGC. For blacks however the marginal contribution of AFQT remains sizeable and positive even after accounting for HGC. This fact is mirrored in the large partial effects of AFQT for blacks, especially relative to whites. These results underline the role of test scores in closing the skill gap between blacks and whites between 1979 and 1997. It also makes the concern about the recent lack of progress in closing the test score gap further (Neal, 2006) even more relevant.

Overall, both the regression and DFL decompositions underline the important role of parental education for understanding the evolution of skills between 1979 and 1997. The partial effects generally attribute about 1/3 to 1/2 of the total increase in skills to parental education, while the marginal effects suggest that more than 2/3 and in some case the entire increase in skills can be explained by the direct and indirect effects of the shift in parental education on wages. We also find important differences across race and gender. Cognitive tests scores of black males improved rapidly, while schooling of black males did not. For black and Hispanic females, we observe a large increase in skills even after accounting for parental education.

8. Evidence on the Stability of Relationship between Unobserved and Observed Skill Characteristics

As we stressed in section 2, our overall assessment of the skills of the 79 cohort relative to the 97 cohort depends upon the assumption A.1 that the conditional distribution of the unobserved determinants of labor market success are the same for the two cohorts: $g(u|z,t) = g(u|z,t')$. We cannot directly test this assumption because u is unobserved. However, if our equating procedure is accurate, then the AFQT test provides a stable indicator of a key component of skill that we can use to test whether the distribution of skills conditional on observable characteristics varies between 79 and 97. If the link between labor market skills and parental education, family structure, and highest grade completed differs across the cohorts, then one would expect the relationship between AFQT and these characteristics to differ as well. We therefore consider here evidence on whether the relation between the AFQT and these characteristics differs across the two cohorts.

If these relationships changed between 1979 and 1997, then we would expect the observed changes in the distribution of parental background, family structure, race and gender to fail to accurately predict the observed changes in the AFQT distribution. Figure 3 compares the observed with the predicted changes in the AFQT distribution. The solid line shows how the observed AFQT score changed across the distribution.[33] The dashed line shows the predicted changes due to re-weighting the 1979 population to match the gender, race and family background composition of the 1997 population. Both the observed and the predicted distribution of the AFQT score improved between 1997 and 1979. The observed and the predicted changes in the AFQT score are largest towards the middle of the distribution. Parental background and family structure variables predict well the overall change in the AFQT score distribution. Based on the parental background variables we predict greater increases towards the bottom of the distribution than were actually observed in the data. However, the predicted changes based on parental education do match the overall features of the observed data. Both the predicted and observed changes of the AFQT-score peak towards the middle of the distribution and for both the changes towards the top of the distribution exceed those toward the bottom by about 2 percentage points. Overall, the figure suggests that the association between AFQT and family background measures has remained fairly constant.

[33]These changes have been smoothed using local polynomial kernel regressions.

We have performed a similar analysis using a highest grade completed as the dependent variable. After reweighting to match the 1997 cohort in the dimensions of gender, race, parental education, and family structure, the education distribution in 1979 is very close to the actual 1997 distribution. If anything, actual highest grade completed has improved more than would be expected given the shifts in the other skill indicators.[34]

Using the pooled 1979 and 1997 data, we have also regressed AFQT on HGC, parental education, family background and whether the individual is enrolled in school at age 22. We used the full set of race gender interactions that appear in our propensity score model, an indicator for the 1997 sample, and interactions between the 1997 sample indicator and hgc, father's hgc, mother's hgc, and the dummy variables for family structure. The interaction terms indicate whether the slopes relating the conditional mean of AFQT to the other skill measures differs across cohorts. None of the interaction terms are individually significant at the .25 level, and the variables are jointly insignificant.[35] For example, the effect of mother's highest grade completed is only .084 (.114) higher for the 1997 cohort, while the effect of father's hgc is only .091 (.085) lower. The "effect" of hgc on AFQT declines by -.192 (.205). If we exclude the interaction between hgc and the 1997 cohort indicator we obtained similar results for the family background variables.

In summary, there is little evidence that the relationship between AFQT and hgc and family structure has change substantially across cohorts. Nor is there much evidence that the link between AFQT and hgc has changed substantially conditional on the other variables. Assumption A.1 is almost certainly false, but the stability of the link between AFQT and the other skill indicators provide some indication that it is a reasonable approximation.

9. CONCLUSION

Changes in the level and distribution of skill play an important role in determining both economic growth and changes in the distribution of wages and employment. In this paper we examine changes in the characteristics of American youth between the late 1970s and the late 1990s, with a focus on characteristics that matter for labor market success. Drawing on the approach of DFL, we reweight the NLSY79 to look like the NLSY97 along a number of dimensions that are related to labor market success, including race, gender, parental background, education, test scores, and variables that capture whether individuals transition smoothly from school to work. We then use the reweighted sample to examine how changes in the distribution of observable skills affect employment and wages. We also use regression methods to assess the labor market consequences of differences between the two cohorts.

[34]

	Highest Grade Completed at 22					
	8	11	12	14	16	17
actual 1979	2.9	15.7	41.2	18.5	21.3	0.39
reweighted 1979	2.3	14.4	34.2	22.2	26.2	0.7
actual 1997	2.0	12.3	35.9	21.0	28.4	0.4

[35]These results are is robust to working with subsets of the interactions.

Considering the entire population, we find that the current generation is more skilled than the previous one, but also that the skill distribution in the current generation has widened. Much of change seems to be generated by changes in the distribution of parental education. Our evidence suggests that skills for all groups combined have increased by only small amounts once we account for the change in skills that can be attributed to parental education. Hispanics are an exception to this finding.

Interestingly, we find that the skill gaps between white males and other demographic groups have declined over this time-period. If the wage process faced by the NLSY79 cohort in their prime age years persists, our findings imply that women will gain significantly relative to men. Significant skill gaps remain, but blacks and Hispanics have narrowed the gap in skills relative to whites.

We doubt that our empirical findings will be the last word on change in labor force skills. First, more needs to be done to assess the issue of whether the NLSY97 base year sample is nonrepresentative. Second, while we believe that our corrections for attrition and for bias from missing data on test scores are adequate, one might be able to improve upon them by using a larger set of covariates from the base year sample at the cost of greater sampling error. Third, our analysis of the NLSY79 and NLSY97 could be supplemented with information from other sources, including the NAEP and the CPS. Magnuson and Waldfogel's (2008) recent analysis of the NAEP test scores for the relevant years indicate that they move in the same direction as the AFQT scores. We are currently extending our analysis to other outcomes, notably incarceration and fertility. We will also explore the role of immigration in shaping the labor market potential of the cohort represented by NLSY97, as well as the impact of immigrants who arrived in the US between the ages of 17 and 22.

In future work, we hope to extend our methods in two directions. The first involves using vectors, say Z_1 and Z_2, of variables for which the joint distribution is available in the NLSY79 but only the marginal distributions of Z_1 and Z_2 are observed for the NLSY97. The second involves using variables that measure the same concepts but are based on different questions in the two data sets.

10. References

Bishop, John H., "Is the Test Score Decline Responsible for the Productivity Growth Decline?", *The American Economic Review*, Vol. 79, No. 1. (March): pp. 178-197.

Blau, Francine D. And Andrea H. Beller. 1992. "Black-White Earnings Over the 1970s and 1980s: Gender Differences in Trends." *Review of Economics and Statistics*. Vol 74:2, pp276-86.

Belley, Philippe and Lance Lochner, (2007) “The Changing Role of Family Income and Ability in Determining Educational Achievement”, University of Western Ontario.

Card, David and Alan Krueger (1996). “School resources and student outcomes: an overview of the literature and new evidence from North and South Carolina”. *Journal of Economic Perspectives* 10(4), 31-50.

Cascio, Elizabeth and Ethan Lewis (2006) "Schooling and The Armed Forces Qualifying Test. Evidence from School-Entry Laws", *The Journal of Human Resources*, XLI, 2: 294-318.

Chin, Aimee and Hoyt Bleakley, “Language Skills and Earnings: Evidence from Childhood Immigrants." *Review of Economics and*
Statistics, (2004), 86(2): 481-496.

Chinloy, Peter, (1980)"Sources of Quality Change in Labor Input," *American Economic Review*, 70, March, 108-19.

Denison, E.F, (1974), “Accounting for United States economic growth”, 1929-1969, Brookings Institution, Washington.

DiNardo J, Fortin NM, Lemieux T (1996) "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach", *Econometrica* 64(5): 1001-46

Eide, Eric, and Jeff Grogger 1995. "Changes in College Skills and the Rise in the College Wage Premium". *Journal of Human Resources* v30 n2 Spring pp 280-310.

Firpo, Sergio, Nicole Fortin and Thomas Lemieux, (2007) "Unconditional Quantile Regressions", unpublished paper, University of British Columbia.

Gosling, A., Machin, S., and C. Meghir (2000) "The changing distribution of male wages in the UK", *Review of Economic Studies* 67: 635-686.

Grogger, Jeffrey (1996) "Does School Quality Explain the Recent Black/White Wage Gap", *Journal of Labor Economics* Vol 14(2): 231-253.

Heckman, James and Paul LaFontaine (2007), "The American High School Graduation Rate: Trends and Levels", IZA Working Paper No. 3216.

Hirano, Keisuke, Guido Imbens, and Geert Ridder, (2003) "Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score" *Econometrica*, 71(4): 1161-1189.

Jorgensen, Dale, Frank Gollop, and Barbara Fraumeni, (1987), “Productivity and U.S. Economic Growth”. Cambridge, MA: Harvard University Press.

Juhn, C., K. M. Murphy, and B. Pierce (1991) "Accounting for the Slowdown in Black-White Wage Convergence." in Workers and their Wages: Changing Patterns in the United Stats. Ed. Marvin H. Kosters, AEI Press, Washington, DC: 107-143.

Korenman, S., & Winship, C. (2000). "A reanalysis of The Bell Curve: Intelligence, family background, and schooling." In K. Arrow & S. Bowles & S. Durlauf (Eds.), Meritocracy and Economic Inequality. Princeton: Princeton University Press.

Machado, Jose and Jose Mata (2005) "Counterfactual Decomposition of Changes in Wage Distributions Using Quantile Regression", *Journal of Applied Econometrics* 20: 445-465.

MaCurdy, Thomas and Edward Vytlacil (2003) "Establishing New Norms for the AFQT Using Data from PAY97", Working Paper.

Melly, Blaise (2005), "Decomposition of differences in distribution using quantile regression", *Labour Economics* 12: 577-590.

W. Moore, S. Pedlow, P. Krishnamurty, and K. Wolter (2000), "National Longitudinal Survey of Youth 1997 (NLSY97) Technical Sampling Report", NCES (National Center for Education Statistics) (2005). Long-term trend major results. July 2005. Available at http://nces.ed.gov/nationsreportcard/ltt/results2004/, accessed September 2007.

Neal, D. 2006. "Why has black-white skill convergence stopped?" In *The Handbook of Economics of Education*, vol. 1, ed. E. Hanushek and F. Welch. Amsterdam: North-Holland.

Segall, D. O. (1997). "Equating the CAT-ASVAB". In W. A. Sands, B. K. Waters, & J. R. McBride (Eds.), *Computerized adaptive testing: From inquiry to operation* (pp. 181-198). Washington, DC: American Psychological Association.

Smith, J. and Welch, F. 1989. Black economic progress after Myrdal. *Journal of Economic Literature* 27, 519-64.

11. Appendix A: Data Appendix

11.1. **Sample Selection.**

- The NLSY79 is drawn from the resident US population of 14-21 year olds, while the NLSY97 samples from the resident population aged 12-16.[36] Consequently, the NLSY79 includes immigrants who arrive after age 16 while the NLSY97 does not. We need to adjust for these differences in scope because skills vary with age of arrival. Using census data and also data from the NLSY79, we examined the variation in skills by age of arrival for the Hispanic population. Observable skills of those arriving at older ages are much lower than those arriving at younger ages. We adjust the weights for the NLSY79 to match the scope of the NLSY97, dropping 96 individuals from the NLSY79 who first entered the US between age 16 and 21. Individuals who migrated into the US prior to age 12 are equally weighted. Those who migrated at earlier ages are weighted by the ratio of the probability of being observed in 1997 to the probability for 1979. This implies weights of 4/5 for those arriving at age 13, 3/5 for age 14, 16/35 for age 15 and 4/15 for age 16. When we refer to the BLS base year weights in the text and tables, we mean the adjusted weights.
- We exclude the economically disadvantaged non-black/non-Hispanic supplemental sample and the military supplemental sample from the analysis of the NLSY79. The non-black/non-Hispanic oversample and most of the military sample were discontinued in 1990 and 1984 respectively, and so do not provide labor market outcomes in the age range that we use. We drop 83 individuals with race/ethnicity code "other" from the NLSY97, since no comparable category exists in NLSY79. In the NLSY79 there are 3,650 people in the supplemental sample of blacks and non-Hispanics and 6,111 in the cross-section. In the NLSY97 the supplemental and cross-section samples contain 2,236 and 6,712 respondents respectively.[37]
- In both surveys we construct our skill measures in a similar manner using the waves up to the survey year when these individuals were 22. We retain the observation that is closest to 22 years and 6 month old and then measure variables such as highest grade completed and early work experience by reference to this observation.[38] While all base

[36]We exclude 4 individuals born before 1957 or after 1964 from the NLSY79.

[37]In constructing weights we account for excluding the non-black/non-Hispanic sample by using the cross-section weights for whites and the weights for the combined cross-section and supplemental sample of blacks and Hispanics. Excluding the military does lead to a difference with the population represented by NLSY97, which was too young to be in the military when the sample was constructed but may have entered between the ages of 17 and 21 and thus would have been in scope for the NLSY79 military supplement. According to the NLSY documentation, 51 persons who might have been included as part of a representative sample of youth including the military were continued, as were an additional 150 observations. In principle, we could include these observations and construct base year weights that make the sample representative of the non- institutionalized youth population aged 14-22 in 1979, including the military. Since the military is a very small fraction of the total, we doubt this would make much difference.

[38]The interviews of a given individual are not exactly one year apart. Consequently, some individuals respond twice at age 22 and some do not respond at age 22 but instead are surveyed twice at age 21 or twice at age 23.

year respondents of the NLSY79 cohort have reached age 22, only cohorts 1980-1983 and a few respondents from cohort 1984 had turned 22 by the 2005 survey. We have a sample of 9,661 respondents for the NLSY79 cohorts and 7,148 respondents for the NLSY97 who should have been observed at age 22.

- Appendix table A.1 summarizes the retention patterns for our sample in the NLSY97 and the NLSY79. There are 9,661 (7,148) individuals in the NLSY79 (NLSY97) who should have been observed at age 22 and thus fall within the scope of our study. As mentioned above this excludes the oversampled white males and females and the military sample as well as those who migrated to the US after age 16. A total of 9,228 (6,085) respondents within the scope of our study were actually observed at age 22. A negligible 27 (71) are lost due to missing information on highest grade completed. This leaves 9,201 (6,014) observations. Non-participation in the ASVAB eliminates an additional 379 (1,132) respondents. We retain a total of 8,822 NLSY79 respondents and 4,882 NLSY97 respondents, which constitute 91.32% of the total eligible sample in the NLSY79 but only 68.30% for the NLSY97.[39]

11.2. **Variables used and their construction.**

- Base Year Weights: In the case of NLSY79, we use the 1979 cross section weights in the case of whites (R0216101) and the 1979 combined cross-section and supplemental sample weights for blacks and Hispanics. In the case of NLSY97 we use the base year weights for the combined cross section and supplemental sample. We adjust the weights of immigrants based on age as described in the text.
- Work after graduation (1979 & 1997): We construct this variable in the following manner. We examine a person when she is 22 or 23 years of age at the time of the interview and note her highest grade completed. (Due to variation in the timing of interviews, age may increase by 0, 1, or 2 between surveys.) If she had achieved the same highest grade completed by the age of 20 or less, we consider her to be in the universe of people who could have worked after "graduation" ($workuniv = 1$). The variable $work$ is coded as 1 if $workuniv = 1$ and the individual have reported 14 weeks of work or more in either of the first 2 years after graduation. It is coded as 0 otherwise.
- Timing of school completion (1979 & 1997): Again, the universe we consider are the people whose highest grade completed at age 22 or 23 is the same as the highest grade completed by age 20 or below. ($workuniv = 1$). For these individuals, $ontime = 1$ if the age when last in school equals highest grade completed by June plus six and 0 otherwise. (School completion is assumed to occur in June of given year.) The dummy $early = 1$ if school leaving age is less than highest grade completed as of June plus six. $late = 1$ if school leaving age exceeds the highest grade completed in June plus six.

We retain the observation that is closest to 22 years and 6 month old and then measure variables such as highest grade completed and early work experience as of this age=22 observation.

[39] Missing values for other explanatory variables, such as mother's education, are coded as a separate category so that we are able to maintain maximum coverage for our sample.

- AFQT scores. Two major problems arise in making the AFQT-scores comparable across the NLSY79 and NLSY97 cohort. First, the ASVAB changed from a paper and pencil (P&P) format in 1980 to a computer administered (CAT) format in 1997. Second, NLSY79 sample members were between 15 and 23 years old when they took the test. Test takers in the NLSY97 were between 12 and 18 years olds and thus typically were younger than their NLSY79 counterparts.

To make the AFQT scores comparable we perform two "equipercentile" procedures. The first method is based on the work of Daniel Segall (1997), who matches test scores of individuals across percentiles based on a study of individuals who were randomly administered either the P&P or the CAT. As noted above, Segall kindly provided us with the results of mapping within age P&P (1979) scores for the NLSY79 sample into equivalent CAT (1997) scores The second equipercentile procedure adjusts for the variation in age at test taking. For this purpose we use the overlap between the age ranges of NLSY79 and NLSY97 test takers. The most overlap exists for age 16 with 1329 respondents in 1997 taking the test at age 16 and 1324 respondents in 1980 taking the test at age 16. For each sample, we perform an equipercentile mapping to age 16 of the scores of respondents who took the test age other ages. Specifically, in the case of the NLSY79 sample, persons who took the test at age a who scored in the q'th percentile among age a test takers were assigned the q'th percentile value for NLSY79 sample members who took the test at age 16. A corresponding set of assignments were made for the NLSY97 sample. This procedure assumes that the relative ranking of individuals in the AFQT-distribution on average does not depend on when they took the test. It also assumes that the level of cognitive skills in adulthood associated with the q'th percentile in the age 16 test taker distribution is the same as that for the q'th percentile in the age a distribution.

Table B.1 provides evidence that the joint distribution of observables and the AFQT score is indeed similar across ages in both surveys. We estimate regressions of the standardized AFQT-scores on interaction of the birth years with various observables used in the analysis. If the joint distribution of observables and percentile score conditional on age at the time of the test depends on age, then we would expect that interacting age (or equivalently birth-year) with the other observables would help predict the age standardized AFQT scores. Table B.1 reports the F-statistic for excluding various sets of interactions between observables and birth years for various specifications and both the NLSY79 and NLSY97. There is no evidence in either data set that the relationship between the observables and the standardized AFQT score varies with age at the time of the test.[40]

- Presence of biological parents at age 14: ($mom\_only, dad\_only, mom\_dad, \ neitherMom\_Dad$).[41] In 1979 this variable is constructed using a retrospective question to age 14 [R0001900]. In 1997 the variable [R1205300] is constructed using the household roster generated

[40] The NLSY 1997 data files do not include an AFQT score as constructed from the full ASVAB battery in accordance with the procedure used by the Department of Defense. They do include a self created variable that mimics what the DOD does to various parts of the CAT-ASVAB. It is not comparable to the AFQT in 1979.

[41] Respondents living with "neither" parent were typically living with grandparents or other relatives.

based on the screener interview. In 1997 this variable therefore refers to the age of respondents during the screening interview - typically between 12 and 16. In 1979 and 1997 there are 19 and 31 respondents respectively in the full sample for whom this information is missing. We assign these individuals to the largest category (living with both biological mother and father).

- Race: Information on race and ethnicity is taken from the screener interviews. In both surveys the variable combines ethnicity and race information and gives priority to Hispanic ethnicity over race classification.
  - 1979 [R02147.00]: The 1979 race/ethnicity code does not allow for mixed race.
  - 1997 [R14826.00]: The 1997 race/ethnicity code allows for mixed race/other classification. 83 respondents fall into this category. We eliminate these from the analysis since there is no counterpart in the 1979.
- Mother's Highest Grade Completed, Father's Highest grade Completed. In both cohorts, we use the same strategy to identify father and mother's highest grade completed. The variables are based on a screener interview question. If the response to the screener question in 1979 and 1997 is missing, we use the demographic roster information collected each year.
- Wage: The actual wage variable used for the 1979 cohort is the hourly wage variable. This variable denotes the hourly wage in cents and has been CPI adjusted for 2003. We recoded real wage values below \$3.00 as \$3.00 and values above \$200.00 as \$200.00. We used a regression procedure to standardize for experience and secular trends. For the 1979 cohort we compute experience and education adjusted wages as follows. We first regress the log of hourly wage on a cubic of potential experience (defined as age minus highest grade completed at age 22 minus 6) by education group. Education groups are less than 12 years of education, exactly 12 years of education and more than 12 years of education. From these regressions we compute the predicted log wage for a common experience of 23 and year 2002 and add the residual. In this manner we regression adjust wages to correspond to 2002 and experience equal to 23.
- High School Diploma and GED Information: In 1979 a question is asked each year whether the person has a GED or a HS diploma (respondents can also answer both, but there are so few of them that we include these respondents under the HS Diploma category). If they respond in the affirmative, then they were asked when they received the HS Diploma or GED. We use answers to these questions to construct indicators for HS Diploma and for GED by age 22. If the respondent reported a degree one year but not in the following year, then we assign the degree report in the prior interview. Hence if someone responds affirmatively to having a degree once, then that person is assumed to have degree for the rest of their time in the sample. In the 1997 sample, we use the answers to questions about the highest degree completed to back out whether a person received a HS Diploma or a GED by age 22.

Appendix B: Family Structure in the NLSY Samples and in the Census

Based on the NLSY79 and the NLSY97 we report a sizeable decline in the fraction of children living with their families during adolescence. This appendix compares our findings with statistics on the family structure between 1980 and 2000 generated using 14 years olds from the combined 1 and 5% IPUMS samples in both census years. The IPUMS allows one to generate a measure of social parenthood but not biological parenthood. This measure includes step-parents and adoptive parents. It is generated based on an algorithm exploiting various survey responses from the Census on questions regarding family structure, age, whether a women has given birth, how many children survived, last name and other indicators (see www.ipums.org). This algorithm changes over time and it is not clear how comparable the variables are. The measures of family structure from the NLSY used throughout the paper refer to biological parenthood and are based on survey responses obtained during the screening interview. Due to differences in the questions, it is possible to construct measures that are strictly comparable across cohorts only for the biological parent structure. However, we can also generate an approximate social measure based on the survey responses. The ambiguity arises because in 1997 we can not distinguish individuals living with one vs. two adoptive parents if they do not have biological parents. This problem arises only for a small number of cases (103) and we assign them to the largest group - both mother and father present. Note that the family structure question in 1979 is retrospective and refers to family structure at age 14. The family structure measures for the 1997 cohort are obtained during the screening interview and refer to the age at the screening interview, i.e. 12-16 years of age. Table C reports the social family structure measures for 1980-2000 from the IPUMS sample and the biological and social family structure measures from the 1979 and 1997 NLSY cohort. The IPUMS statistics are weighted by the weights (perwt) provided by the Census and the NLSY variables are weighted by the cross-sectional weights.

The results in Table C provide additional evidence for the break-up of the traditional family. The results from the NLSY and from the Census are roughly consistent, even though in the NLSY we typically find more individuals living with two (social) parents.

Table 1 Characteristics by Attrition Status at Age 22

	NLSY 1979					*NLSY 1997*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	N	Pooled	Attriters	Stayers	Attriters-Stayers	N	Pooled	Attriters	Stayers	Attriters-Stayers
Race										
White	4,899	78.90%	79.82%	78.86%	0.96 (2.04)	3,741	71.19%	75.30%	70.42%	4.88 (1.47)***
Black	2,911	14.75%	11.84%	14.89%	-3.05 (1.78)*	1,895	15.68%	13.44%	16.09%	-2.65 (1.18)***
Hispanic	1,851	6.35%	8.35%	6.25%	2.10 (1.22)*	1,512	13.13%	11.25%	13.48%	-2.23 (1.10)**
Sample										
Cross-Sectional Sample	6,082	84.64%	83.74%	84.68%	-0.94 (1.81)	5,352	87.07%	90.04%	86.52%	3.52 (1.09)***
Supplemental Sample	3,579	15.36%	16.26%	15.32%	0.94 (1.81)	1,796	12.93%	9.96%	13.48%	-3.52 (1.09)***
Parental Years of Schooling										
Father										
Years completed (average)	8,215	12.09	12.19	12.09	0.10 (0.18)	6,115	13.07	12.92	13.10	-0.18 (0.11)*
Missing	1446	10.00%	13.24%	9.84%	3.40 (1.50)**	1,033	10.84%	11.35%	10.74%	0.61 (1.01)
Mother										
Years completed (average)	9,038	11.78	11.73	11.79	-0.06 (0.13)	6,886	13.01	12.73	13.06	-0.33 (0.09)***
Missing	623	5.12%	7.14%	5.03%	2.11 (1.10)*	262	3.05%	3.38%	2.99%	0.39 (0.56)
Parental Presence at age 14										
Mother only	2,378	18.54%	18.69%	18.54%	-0.15 (1.95)	2,817	35.67%	32.64%	36.24%	-3.60 (1.56)**
Father only	278	2.98%	4.09%	2.93%	1.16 (0.85)	418	6.36%	7.35%	6.18%	1.17 (0.79)
Mother and Father	6,545	75.38%	73.33%	75.48%	-2.15 (2.16)	3,473	52.75%	54.37%	52.45%	1.92 (1.62)
Neither Mother nor Father	460	3.09%	3.89%	3.05%	0.84 (0.87)	440	5.22%	5.64%	5.14%	0.50 (0.72)
Total	9,661		4.57%	95.43%		7,148		15.74%	84.26%	

Reported statistics are generated by attrition status at age 22 and weighted using the the base year sample weights for NLSY79 and NLSY97 respectively adjusted for year of entry into the US. For each statistic the difference between attriters and stayers is reported along with standard errors. Difference statistically significant at the .01 level (***), .05 level (**) or .10 level (*). Std errors reported in parenthesis.

Table 2: Skill indicators/early outcomes by AFQT Missing status

Sample: persons observed at age 22

	NLSY 1979					NLSY 1997				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	N	Pooled	AFQT Missing	AFQT Not Missing	Missing-Not Missing	N	Pooled	AFQT Missing	AFQT Not Missing	Missing - Not Missing
Race										
White	4,674	78.95%	78.21%	78.98%	-0.77 (2.21)	3,115	71.35%	62.74%	73.17%	-10.42 (1.52)***
Black	2,808	14.74%	12.45%	14.84%	-2.38 (1.92)***	1,655	15.55%	18.68%	14.89%	3.78 (1.22)***
Hispanic	1,746	6.31%	9.34%	6.19%	3.15 (1.32)***	1,315	13.10%	18.58%	11.94%	6.63 (1.14)***
Sample										
Cross Sectional Sample	5,819	84.75%	84.18%	84.77%	-0.59 (1.95)	4,505	86.93%	81.76%	88.03%	-6.27 (1.14)***
Supplemental Sample	3,409	15.25%	15.82%	15.23%	0.59 (1.95)	1,580	13.07%	18.24%	11.97%	6.27 (1.14)***
Highest grade completed at age 22										
Years completed (average)	9,201	12.64	11.82	12.68	-0.85 (0.11)***	6,014	13.12	12.56	13.23	-0.67 (0.07)***
Missing	27	0.29%	0.52%	0.28%	0.24 (na)	71	0.92%	1.24%	0.85%	0.38 (0.32)
Parental Years of Schooling										
Father										
Years completed (average)	7,858	12.09	11.63	12.11	-0.48 (0.19)**	4,814	13.12	12.55	13.23	-0.68 (0.12)***
Missing	1,370	9.94%	13.01%	9.81%	3.20 (1.62)**	1,271	16.19%	21.43%	15.09%	6.34 (1.24)***
Mother										
Years completed (average)	8,639	11.78	11.36	11.8	-0.44 (0.14)***	5,746	13.02	12.33	13.16	-0.83 (0.09)***
Missing	589	5.09%	8.66%	4.94%	3.72 (1.19)***	339	4.53%	6.04%	4.21%	1.83 (0.70)***
Parental presence at age 14										
Mother only	2,268	18.55%	16.09%	18.66%	-2.56 (2.11)	2,431	35.93%	40.09%	35.05%	5.04 (1.62)***
Father only	263	2.93%	3.99%	2.89%	1.09 (0.91)	343	6.21%	7.22%	6.00%	1.22 (0.81)
Mother and Father	6,260	75.43%	75.33%	75.44%	-0.11 (2.33)	2,943	52.84%	45.73%	54.34%	-8.61 (1.68)***
Neither Mother nor Father	437	3.08%	4.60%	3.01%	1.58 (0.94)*	368	5.02%	6.96%	4.61%	2.34 (0.74)***
Total	**9,228**		**5.92%**	**84.08%**		**6,085**		**19.98%**	**80.02%**	

Reported statistics are generated for groups defined by whether AFQT test score is missing. They are weighted using the attrition adjusted weights generated by the authors to account for attrition by age 22. For each statistic the difference between the attriters and stayers is reported. * significant at the .10 level, Difference statistically significant at the .01 level (***), .05 level (**) or .10 level (*). Std errors reported in parenthesis.

Table 3 Summary Statistics

Panel A: Statistics for Full Sample

Variable	1979	1997	Difference (1997-1979)
AFQT	42.35	44.19	1.84 (0.47)***
HGC at age 22	12.64	13.02	0.38 (0.03)***
GED at age 22	5.80%	7.28%	1.48 (0.41)***
HS Diploma at age 22	78.54%	80.15%	1.61 (0.68)**
HGC>=14 at age 22	31.11%	39.79%	8.68 (0.79)***
Enrolled at age 22	20.38%	29.95%	9.57 (0.71)***
Father's HGC	12.09	12.81	0.72 (0.05)***
Mother's HGC	11.77	12.71	0.94 (0.04)***
Mother only	18.57%	35.66%	17.09 (0.68)***
Father only	3.02%	5.94%	2.92 (0.32)***
Mother and Father	75.23%	52.98%	-22.25 (0.73)***
Neither Mother nor Father	3.18%	5.42%	2.24 (0.31)***
Work after leave school	83.11%	84.94%	1.83 (0.91)**

Panel B: Statistics by race

Variable	White			Black			Hispanic		
	1979	1997	Difference (1997-1979)	1979	1997	Difference (1997-1979)	1979	1997	Difference (1997-1979)
AFQT	48.08	50.44	2.36 (0.64)***	18.75	25.45	6.7 (0.61)***	26.06	32.2	6.14 (0.87)***
HGC at age 22	12.81	13.26	0.45 (0.05)***	12.11	12.41	0.30 (0.06)***	11.71	12.54	0.83 (0.07)***
GED at age 22	5.50%	6.87%	1.37 (0.58)***	6.86%	10.13%	3.27 (0.84)***	7.11%	6.10%	-1.01 (0.92)
HS Diploma at age 22	81.63%	83.02%	1.39 (0.93)	68.98%	71.50%	2.52 (1.39)*	62.34%	76.40%	14.06 (1.67)***
HGC>=14 at age 22	33.91%	45.30%	11.39 (1.17)***	21.59%	27.06%	5.47 (1.30)***	18.45%	28.49%	10.04 (1.59)***
Enrolled at age 22	21.83%	32.81%	10.98 (1.05)***	14.67%	22.51%	7.84 (1.16)***	15.54%	24.96%	9.42 (1.52)***
Father's HGC	12.48	13.35	0.87 (0.07)***	10.64	12.29	1.65 (0.09)***	9.59	10.52	0.93 (0.14)***
Mother's HGC	12.12	13.2	1.08 (0.05)***	11.00	12.43	1.43 (0.07)***	9.07	10.69	1.62 (0.12)***
Mother only	14.27%	30.32%	16.05 (0.96)***	38.21%	59.51%	21.30 (1.49)***	27.10%	35.21%	8.11 (1.73)***
Father only	3.13%	6.52%	3.39 (0.49)***	2.65%	4.82%	2.17 (0.57)***	2.49%	4.45%	1.96 (0.68)***
Mother and Father	80.61%	58.62%	-21.99 (1.05)***	50.21%	25.34%	-24.87 (1.44)***	65.55%	56.06%	-9.49 (1.82)***
Neither Mother nor Father	1.99%	4.54%	2.55 (0.40)***	8.93%	10.33%	1.40 (0.90)**	4.86%	4.28%	-0.58 (0.74)
Work after leave school	86.81%	88.11%	1.30 (1.23)*	68.39%	74.71%	6.32 (1.93)***	79.54%	84.22%	4.68 (2.03)**

Notes: Weighted means presented. Weights used are attrition-afqt adjusted weights created by the authors. Summary stats do not condition on presence at age 22, except for variables which are measured at age 22 (HGC and Enrollment). The 1997 data has another race category "Other" . Due to small numbers in that category we do not display it in th table. Difference statistically significant at the .01 level (***), .05 level (**) or .10 level (*). Std errors reported in parenthesis.

Table 4: Summary Statistics by Race and Gender

Males	White			Black			Hispanic		
	1979	1997	Difference (1997-1979)	1979	1997	Difference (1997-1979)	1979	1997	Difference (1997-1979)
AFQT	48.57	50.05	1.48 (0.94)	17.95	23.55	5.60 (0.89)***	27.51	32.39	4.88 (1.30)***
HGC at age 22	12.74	13.04	0.28 (0.07)***	11.89	12.06	0.17 (0.08)***	11.7	12.45	0.75 (0.101)***
GED at age 22	5.81%	8.05%	2.24 (0.85)***	8.22%	12.90%	4.68 (1.31)***	8.59%	6.55%	-2.04 (1.34)
HS Diploma at age 22	79.90%	81.40%	1.50 (1.35)	64.20%	64.56%	0.35 (2.07)	60.27%	75.32%	15.05 (2.44)***
HGC>=14 at age 22	33.27%	39.43%	6.16 (1.63)***	18.16%	20.89%	2.73 (1.71)	18.03%	24.48%	6.45 (2.23)***
Enrolled at age 22	24.51%	30.89%	6.38 (1.51)***	13.21%	17.45%	4.24 (1.54)***	15.61%	25.61%	10.00 (2.22)***

Females	White			Black			Hispanic		
	1979	1997	Difference (1997-1979)	1979	1997	Difference (1997-1979)	1979	1997	Difference (1997-1979)
AFQT	47.58	50.85	3.27 (0.88)***	18.93	27.38	8.45 (0.84)***	24.59	31.98	7.39 (1.16)***
HGC at age 22	12.89	13.51	0.62 (0.07)***	12.33	12.78	0.45 (0.08)***	11.71	12.66	0.95 (0.11)***
GED at age 22	5.18%	5.62%	0.44 (0.77)	5.54%	7.15%	1.61 (1.04)	5.62%	5.48%	-0.14 (1.18)
HS Diploma at age 22	83.40%	84.75%	1.35 (1.26)	73.63%	78.97%	5.34 (1.84)	64.41%	77.88%	13.47 (2.29)
HGC>=14 at age 22	34.55%	51.55%	17.00 (1.67)	24.91%	33.69%	8.78 (1.93)	18.87%	34.02%	15.15 (2.28)
Enrolled at age 22	19.09%	34.85%	15.76 (1.46)***	16.08%	27.95%	11.87 (1.73)***	15.46%	24.07%	8.61 (2.07)***

Notes: See Table 3.

Table 5: Comparison of Actual Employment Rates of 1979 Cohort with Counterfactual Rates based on characteristics of 1997 cohort.[1]						
	Observed LFP in NLSY 79		Counterfactual minus observed LFP-Rates[3]			
			Model 6[3]	Model 4[3]		Model 5[3]
Percentile	AFQT Sample	Full Sample	AFQT Sample	AFQT Sample	Full Sample	AFQT Sample
All Males	0.919	0.917	0.005	0.001	0.005	0.001
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
White Males	0.931	0.930	0.001	0.001	0.003	-0.001
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Black Males	0.854	0.849	0.027	0.001	0.012	0.008
	(0.009)	(0.009)	(0.010)***	(0.010)	(0.010)	(0.010)
Hispanic Males	0.909	0.902	0.022	0.018	0.031	0.022
	(0.009)	(0.010)	(0.008)***	(0.008)**	(0.007)***	(0.008)***
All Females	0.838	0.837	-0.007	-0.006	-0.004	-0.006
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
White Females	0.841	0.840	-0.015	-0.010	-0.009	-0.012
	(0.007)	(0.007)	(0.009)*	(0.008)	(0.008)	(0.008)
Black Females	0.832	0.830	0.014	0.007	0.011	0.015
	(0.009)	(0.009)	(0.015)	(0.012)	(0.012)	(0.011)
Hispanic Females	0.821	0.819	0.024	0.012	0.018	0.016
	(0.011)	(0.012)	(0.014)*	(0.012)	(0.012)	(0.012)
All groups	0.877	0.876	-0.001	-0.001	0.002	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

1) Employment Rate is measured by reference to a valid wage observation. An individual is coded to have a valid wage observation if the average hourly rate of pay lies between $3 and $200 (in 2003 real values) in a given year. Reported percentages refer to shares with valid wages in years with positive responses between 1998-2004. The AFQT sample includes only respondents with valid AFQT scores. The full sample also includes those with missing AFQT scores. All statistics are weighted by the cross-sectional weights. Specifications estimated on the AFQT sample are in addition weighted to account for both attrition by age 22 and AFQT-non response. Specifications estimated on the full sample are weighted to account for attrition by age 22. Standard errors are bootstrapped with 300 repetitions. Bootstrap stratified on NLSY cohort, race and gender. Units are sampled at the individual level. * refers to significance at 10%, ** at 5%, and *** at 1 % level.

2) Measured against corresponding sample reported in columns 1 and 2.

3) All specifications match on race and gender. Model 4 refers to the specification matching on schooling, parental education and family structure. Model 5 matches schooling, parental education, family structre, and the AFQT-scores. Model 6 refers to the full specification matching on schooling, AFQT scores, parental education, family structure and the school-work transition variables.

Table 6: Comparison of Actual Wages of 1979 Cohort with Counterfactual Wage Distributions Based on Characteristics of 1997 Cohort.[1]

	Observed Wage distribution in NLSY 1979		Counterfactual minus Actual Wages[3]			
			Model 6[3]	Model 4[3]		Model 5[3]
Percentile	AFQT Sample	Full Sample	AFQT Sample	AFQT Sample	Full Sample	AFQT Sample
5%	6.230 (0.030)	6.228 (0.030)	0.023 (0.028)	0.014 (0.028)	0.007 (0.029)	0.014 (0.028)
10%	6.491 (0.011)	6.487 (0.011)	0.019 (0.015)	0.035 (0.014)**	0.031 (0.013)**	0.023 (0.013)*
25%	6.846 (0.009)	6.841 (0.009)	0.049 (0.013)***	0.073 (0.011)***	0.073 (0.010)***	0.063 (0.011)***
50%	7.268 (0.009)	7.265 (0.009)	0.063 (0.013)***	0.081 (0.012)***	0.079 (0.011)***	0.074 (0.012)***
75%	7.665 (0.009)	7.663 (0.008)	0.049 (0.014)***	0.065 (0.015)***	0.061 (0.013)***	0.056 (0.014)***
90%	8.042 (0.014)	8.039 (0.014)	0.088 (0.021)***	0.097 (0.020)***	0.093 (0.020)***	0.094 (0.020)***
95%	8.331 (0.024)	8.327 (0.023)	0.110 (0.033)***	0.129 (0.033)***	0.129 (0.032)***	0.124 (0.033)***
Mean	7.265 (0.008)	7.261 (0.008)	0.058 (0.012)***	0.074 (0.011)***	0.072 (0.010)***	0.067 (0.011)***

1) The AFQT sample includes only respondents with observed AFQT scores. The full sample includes those with missing AFQT scores. Reported wage distributions are conditional on reporting positive wages. Wages are regression standardized to year=2002 and experience=23. Wages are inflation adjusted to 1990 using the CPI-U. All statistics are weighted by the cross-sectional weights. The AFQT sample is in addition weighted to account for attrition by age 22 and AFQT-non response. The full sample is weighted to account for attrition by age 22. Standard errors: bootstrapped with 300 repetitions. Bootstrap stratified on NLSY cohort, race and gender. Units are sampled at the individual level. * refers to significance at 10%, ** at 5%, and *** at 1 % level.

2) Measured against corresponding sample reported in columns 1 and 2.

3) All Specifications match on race and gender. Model 4 refers to the specification matching on schooling, parental education and family structure. Model 5 matches schooling, parental education, family structre, and the AFQT-scores. Model 6 refers to the full specification matching on schooling, AFQT scores, parental education, family structure and the school-work transition variables.

Table 7: Identifying the Contribution of Subsets of Variables to Differences between the 1979 and 1997 Wage Distributions									
Percentile	1979 Log Wage Distribution	Marginal Effects of Additional Variables							
		(1) + Race, Sex	(2) + Family Backgrnd.	(3) + AFQT	(4) + Highest Grade	(5) + Work Transition	Sum of columns (2)-(6)	(3) + Highest Grade	(7) + AFQT
		Model 1	Model 2	Model 3	Model 5	Model 6		Model 4	Model 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
5%	6.230 (0.030)	0.002 (0.006)	0.011 (0.027)	0.000 (0.006)	0.002 (0.015)	0.008 (0.014)	0.023 (0.035)	0.002 (0.013)	0.000 (0.007)
10%	6.491 (0.011)	-0.004 (0.003)**	0.022 (0.013)*	0.004 (0.004)	0.002 (0.007)	-0.004 (0.009)	0.02 (0.018)	0.017 (0.007)***	-0.012 (0.005)***
25%	6.846 (0.009)	-0.006 (0.002)***	0.052 (0.009)***	0.002 (0.004)	0.015 (0.005)***	-0.014 (0.007)**	0.049 (0.014)***	0.026 (0.006)***	-0.010 (0.004)**
50%	7.268 (0.009)	-0.010 (0.003)***	0.056 (0.010)***	0.004 (0.005)	0.024 (0.005)***	-0.011 (0.007)*	0.063 (0.014)***	0.034 (0.006)***	-0.007 (0.004)*
75%	7.665 (0.009)	-0.007 (0.003)***	0.047 (0.011)***	0.003 (0.005)	0.013 (0.007)**	-0.008 (0.006)	0.048 (0.015)***	0.025 (0.008)***	-0.009 (0.005)*
90%	8.042 (0.014)	-0.009 (0.004)***	0.080 (0.019)***	0.004 (0.007)	0.019 (0.009)**	-0.006 (0.007)	0.088 (0.023)***	0.026 (0.011)***	-0.003 (0.006)
95%	8.331 (0.024)	-0.011 (0.006)**	0.107 (0.030)***	-0.002 (0.010)	0.031 (0.013)**	-0.014 (0.010)	0.111 (0.036)***	0.033 (0.016)**	-0.005 (0.009)
Mean	7.265 (0.008)	-0.008 (0.002)***	0.055 (0.009)***	0.002 (0.004)	0.018 (0.005)***	-0.009 (0.005)*	0.058 (0.012)***	0.028 (0.005)***	-0.007 (0.003)**

1. Estimated on AFQT sample (respondents with valid AFQT scores). Reported wage distributions are conditional on reporting positive wages. Wages are regression standardized to year=2002 and experience=23. Wages are inflation adjusted to 1990 using the CPI-U. Standard errors: bootstrapped with 300 repetitions. Bootstrap stratified on NLSY cohort, race and gender. Units are sampled at the individual level. All statistics are weighted by NLSY cross-sectional weights adjusted for attrition by age 22 and non-response to the AFQT variable.

2. Columns 2-8 show the incremental contribution of relevant variables in the title of each column.

Table 8: Identifying the Contribution of Subsets of Variables to Differences between the 1979 and 1997 Wage Distributions by Race and Sex

Percentile	1979 Log Wage Distribution	Marginal Effects of Additional Variables						
		(1) + Family Background	(2) + AFQT	(3) + Highest Grade	(4) + Work Transition	Sum of columns (2) to (5)	(2) + Highest Grade	(6) + AFQT
		Model 2	Model 3	Model 5	Model 6		Model 4	Model 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PANEL A: Males								
	White Male							
10%	6.753	0.049	-0.012	0.010	0.005	0.052	0.015	-0.016
	(0.024)	(0.023)**	(0.012)	(0.012)	(0.017)	(0.033)*	(0.010)	(0.011)
50%	7.490	0.035	-0.016	0.020	-0.005	0.034	0.014	-0.010
	(0.013)	(0.017)**	(0.008)**	(0.007)**	(0.009)	(0.022)	(0.008)*	(0.006)
90%	8.255	0.110	-0.015	0.026	-0.024	0.097	0.023	-0.012
	(0.029)	(0.045)**	(0.016)	(0.021)	(0.016)	(0.054)*	(0.024)	(0.012)
Mean	7.498	0.051	-0.014	0.019	-0.005	0.051	0.021	-0.017
	(0.013)	(0.020)**	(0.008)*	(0.008)**	(0.008)	(0.024)**	(0.010)**	(0.000)
	Black Male							
10%	6.431	-0.015	0.012	0.007	0.010	0.014	0.009	0.010
	(0.023)	(0.027)	(0.010)	(0.012)	(0.025)	(0.040)	(0.014)	(0.009)
50%	7.081	0.064	0.023	0.013	-0.003	0.097	0.016	0.021
	(0.019)	(0.032)**	(0.016)	(0.014)	(0.020)	(0.043)**	(0.015)	(0.013)
90%	7.793	0.129	0.038	0.000	0.002	0.169	0.001	0.036
	(0.031)	(0.040)***	(0.027)	(0.019)	(0.020)	(0.056)***	(0.019)	(0.027)
Mean	7.104	0.057	0.022	0.008	0.001	0.088	0.011	0.019
	(0.018)	(0.025)**	(0.013)	(0.011)	(0.014)	(0.033)**	(0.012)	(0.000)
	Hispanic Male							
10%	6.525	0.039	0.011	-0.001	-0.024	0.025	0.033	-0.022
	(0.027)	(0.037)	(0.015)	(0.018)	(0.024)	(0.049)	(0.018)	(0.015)
50%	7.293	0.095	0.008	0.000	-0.020	0.083	0.026	-0.018
	(0.029)	(0.027)***	(0.013)	(0.012)	(0.016)	(0.036)**	(0.015)	(0.012)
90%	8.040	0.198	0.004	-0.010	-0.045	0.147	0.019	-0.024
	(0.050)	(0.061)***	(0.033)	(0.027)	(0.028)*	(0.079)**	(0.031)	(0.029)
Mean	7.291	0.098	0.006	0.001	-0.027	0.078	0.022	-0.014
	(0.025)	(0.029)***	(0.014)	(0.012)	(0.013)**	(0.037)**	(0.012)	(0.000)

Table 8 (continued): Identifying the Contribution of Subsets of Variables to Differences between the 1979 and 1997 Wage Distributions by Race and Sex								
Percentile	1979 Log Wage Distribution	Marginal Effects of Additional Variables						
		(1) + Family Background	(2) + AFQT	(3) + Highest Grade	(4) + Work Transition	Sum of columns (2) to (5)	(2) + Highest Grade	(6) + AFQT
		Model 2	Model 3	Model 5	Model 6		Model 4	Model 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PANEL B: Females								
	White Females							
10%	6.407	0.005	0.000	-0.002	-0.028	-0.025	0.001	-0.003
	(0.017)	(0.029)	(0.005)	(0.016)	(0.020)	(0.0393)	(0.013)	(0.008)
50%	7.115	0.059	0.001	0.032	-0.019	0.073	0.041	-0.009
	(0.018)	(0.020)**	(0.008)	(0.012)***	(0.011)*	(0.027)***	(0.013)***	(0.007)
90%	7.884	0.050	0.006	0.042	0.016	0.114	0.052	-0.004
	(0.021)	(0.023)**	(0.008)	(0.027)*	(0.014)	(0.039)***	(0.026)**	(0.011)
Mean	7.128	0.039	0.001	0.025	-0.012	0.053	0.034	-0.008
	(0.014)	(0.015)**	(0.005)	(0.009)***	(0.008)	(0.020)***	(0.009)***	(0.000)
	Black Females							
10%	6.359	0.018	0.017	0.004	0.008	0.047	0.017	0.004
	(0.013)	(0.028)	(0.014)	(0.011)	(0.016)	(0.037)	(0.017)	(0.008)
50%	6.936	0.070	0.043	0.011	-0.004	0.12	0.045	0.009
	(0.017)	(0.025)***	(0.026)*	(0.012)	(0.018)	(0.042)***	(0.020)**	(0.021)
90%	7.662	0.072	0.058	0.002	-0.013	0.119	0.030	0.029
	(0.023)	(0.028)***	(0.029)*	(0.012)	(0.012)	(0.044)**	(0.018)*	(0.024)
Mean	6.966	0.060	0.039	0.006	-0.005	0.1	0.032	0.014
	(0.015)	(0.018)***	(0.017)**	(0.008)	(0.010)	(0.028)***	(0.012)***	(0.000)
	Hispanic Females							
10%	6.396	0.040	0.010	0.032	0.009	0.091	0.045	-0.004
	(0.020)	(0.024)*	(0.015)	(0.019)*	(0.026)	(0.042)**	(0.022)**	(0.011)
50%	7.078	0.118	0.025	0.024	-0.012	0.155	0.046	0.003
	(0.026)	(0.026)***	(0.015)*	(0.014)*	(0.016)	(0.036)***	(0.017)***	(0.009)
90%	7.827	0.142	0.052	-0.010	-0.026	0.158	0.027	0.016
	(0.043)	(0.050)***	(0.025)**	(0.018)	(0.030)	(0.067)**	(0.022)	(0.017)
Mean	7.087	0.102	0.033	0.017	-0.008	0.144	0.047	0.003
	(0.023)	(0.024)***	(0.014)**	(0.010)*	(0.014)	(0.033)***	(0.013)***	(0.000)

Table 9: Regression Decompositions, All Groups Combined[1]					
	OLS Regression[2]	Difference in mean characteristics (1997-1979)	Partial Effect of Mean shift on wages	Marginal Effect of Mean Shift on wages	Marginal Effects from DFL (from Table 6.1)
	(1)	(2)	(3)	(4)	(5)
Overall Change			0.040 (0.005)***	0.040 (0.005)***	0.058 (0.012)***
Race and Sex dummies					
White Male	0.195 (0.018)***	-0.035			
Black Male	0.028 (0.019)	0.008			
Hispanic Male	0.186 (0.020)***	0.039	0.008 (0.001)***	-0.009 (0.001)***	-0.008 (0.002)***
White Female	-0.175 (0.018)***	-0.043			
Black Female	-0.131 (0.018)***	0.001			
Parental Years of Schooling					
Mother					
Dummy for missing	0.020 (0.028)	-0.002			
Years of schooling	0.010 (0.003)***	1.186			
Father			0.019 (0.003)***	0.068 (0.004)***	
Dummy for missing	0.055 (0.020)**	0.065			
Years of schooling	0.008 (0.002)***	0.432			0.055 (0.009)***
Parental presence at age 14					
Mother only	-0.044 (0.014)***	0.170			
Father only	0.007 (0.030)	0.029	-0.008 (0.003)***	-0.015 (0.003)	
Neither mother nor Father	-0.032 (0.026)	0.017			
Education					
Highest Grade Completed	0.039 (0.004)***	0.443	0.017 (0.002)***	0.017 (0.001)***	0.028 (0.005)***
AFQT	0.005 (0.000)***	2.367	0.012 (0.001)***	-0.008 (0.001)***	-0.007 (0.003)**
Work Transition					
Work after graduation	0.116 (0.021)***	0.132			
Graduate early	-0.132 (0.024)***	0.101	-0.007 (0.002)***	-0.011 (0.002)***	-0.009 (0.005)*
Graduate on time	-0.148 (0.022)***	0.001			
Graduate late	-0.208 (0.026)***	0.044			
Constant	6.370 (0.046)***				

1) The sample excludes respondents without valid AFQT scores and attriters by age 22. The excluded category in the regression specification refers to white males, with both mother and father present at age 14 and who did not graduate by age 20. Observations are weighted using the cross-section weights provided by the NLSY adjusted to account for attrition by age 22 and AFQT non-response. Standard errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant 10%

2) R-sq = 0.197, F (18, 23865) = 185.48, N = 23884.

Table 10 Panel A: Regression Decompositions for Males by Race [1]

	White				Black				Hispanic			
	OLS Regression Coef	Difference in mean characteristics (1997-1979)	Partial Effect of Mean shift on wages	Marginal Effect of Mean Shift on wages	OLS Regression	Difference in mean characteristics (1997-1979)	Partial Effect of Mean shift on wages	Marginal Effect of Mean Shift on wages	OLS Regression	Difference in mean characteristics (1997-1979)	Partial Effect of Mean shift on wages	Marginal Effect of Mean Shift on wages
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Overall Change			0.028 (0.010)***	0.028 (0.010)***			0.055 (0.013)***	0.055 (0.008)***			0.104 (0.014)***	0.104 (0.008)***
Parental Years of Schooling												
Mother												
Dummy for missing	0.011 (0.056)	-0.008			0.069 (0.058)	-0.027			-0.005 (0.055)	-0.038		
Years of schooling	0.013 (0.005)**	1.244			0.004 (0.006)	1.489			0.025 (0.006)***	2.056		
Father			0.027 (0.006)***	0.072 (0.006)***			0.005 (0.008)	0.058 (0.008)***			0.053 (0.012)***	0.102 (0.010)***
Dummy for missing	0.096 (0.050)**	0.053			-0.029 (0.036)	0.055			-0.009 (0.044)	-0.004		
Years of schooling	0.011 (0.004)***	0.534			0.003 (0.005)	0.841			0.001 (0.005)	1.204		
Parental presence at age 14												
Mother only	-0.072 (0.025)***	0.153			-0.041 (0.024)	0.208			-0.019 (0.035)	0.035		
Father only	-0.031 (0.052)	0.026	-0.013 (0.005)***	-0.022 (0.004)***	-0.124 (0.073)	0.016	-0.011 (0.006)**	-0.016 (0.005)***	0.096 (0.109)	0.035	0.003 (0.004)	-0.001 (0.004)
Neither mother nor Father	-0.041 (0.058)	0.022			-0.041 (0.053)	0.014			-0.052 (0.072)	0.003		
Education												
Highest Grade Completed	0.048 (0.007)***	0.413	0.020 (0.003)***	0.012 (0.001)***	0.059 (0.008)	0.076	0.004 (0.001)***	-0.012 (0.001)***	0.027 (0.010)***	0.584	0.016 (0.006)***	0.016 (0.002)***
AFQT	0.005 (0.000)***	2.308	0.011 (0.001)***	-0.015 (0.001)***	0.008 (0.001)	5.979	0.049 (0.004)***	0.024 (0.002)***	0.005 (0.001)***	5.680	0.031 (0.006)***	-0.008 (0.001)***
Work Transition												
Work after graduation	0.139 (0.043)***	0.169			0.068 (0.037)	0.197			0.155 (0.071)**	0.148		
Graduate early	-0.231 (0.049)***	0.134	-0.017 (0.005)***	-0.020 (0.005)***	0.013 (0.055)	0.146	0.008 (0.008)	0.001 (0.007)	-0.075 (0.080)	0.152	0.002 (0.008)	-0.006 (0.009)
Graduate on time	-0.169 (0.046)***	0.006			-0.062 (0.038)	0.004			-0.293 (0.079)***	0.053		
Graduate late	-0.273 (0.048)***	0.032			-0.077 (0.041)	0.088			-0.225 (0.067)***	-0.027		
Constant	6.404 (0.082)***				6.198 (0.107)				6.641 (0.113)			
R-sq	0.161				0.162				0.149			
Observations	5997				3539				2235			

Table 10 Panel B: Regression Decompositions for Females by Race [1]												
	White				**Black**				**Hispanic**			
	OLS Regression	Difference in mean characteristics (1997-1979)	Partial Effect of Mean shift on wages	Marginal Effect of Mean Shift on wages	OLS Regression	Difference in mean characteristics (1997-1979)	Partial Effect of Mean shift on wages	Marginal Effect of Mean Shift on wages	OLS Regression	Difference in mean characteristics (1997-1979)	Partial Effect of Mean shift on wages	Marginal Effect of Mean Shift on wages
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Overall Change			0.047 (0.009)***	0.047 (0.009)***			0.097 (0.009)***	0.097 (0.004)***			0.132 (0.013)***	0.132 (0.004)***
Parental Years of Schooling												
Mother												
Dummy for missing	0.052 (0.054)	0.012			-0.015 (0.042)	-0.009			-0.003 (0.073)	-0.012		
Years of schooling	0.008 (0.005)	1.310			0.004 (0.005)	1.560			0.009 (0.007)	2.087		
Father			0.025 (0.007)***	0.061 (0.007)***			0.008 (0.007)	0.061 (0.007)***			0.004 (0.013)	0.061 (0.012)***
Dummy for missing	0.123 (0.046)***	0.060			-0.007 (0.027)	0.082			-0.079 (0.039)**	0.052		
Years of schooling	0.010 (0.004)**	0.641			0.003 (0.004)	0.927			-0.012 (0.006)**	0.850		
Parental presence at age 14												
Mother only	-0.061 (0.027)***	0.176			-0.003 (0.021)	0.199			0.120 (0.033)***	0.106		
Father only	0.072 (0.044)*	0.039	-0.008 (0.006)	-0.015 (0.006)***	0.018 (0.054)	0.028	-0.001 (0.005)	-0.010 (0.004)**	0.110 (0.099)	0.015	0.016 (0.004)***	0.015 (0.004)***
Neither mother nor Father	0.009 (0.068)	0.015			-0.043 (0.030)	0.017			-0.100 (0.063)*	-0.015		
Education												
Highest Grade Completed	0.022 (0.007)***	0.704	0.015 (0.005)***	0.020 (0.002)***	0.046 (0.007)***	0.487	0.022 (0.003)***	0.020 (0.001)***	0.057 (0.009)***	0.829	0.048 (0.008)***	0.054 (0.005)***
AFQT	0.004 (0.001)***	4.406	0.018 (0.002)***	-0.011 (0.001)***	0.010 (0.001)***	7.237	0.070 (0.006)***	0.035 (0.003)***	0.007 (0.001)***	7.644	0.056 (0.007)***	0.006 (0.001)***
Work Transition												
Work after graduation	0.106 (0.047)***	0.056			0.143 (0.027)***	0.158			0.083 (0.041)**	0.165		
Graduate early	-0.118 (0.048)**	0.048	-0.003 (0.003)	-0.007 (0.003)**	-0.100 (0.036)***	0.102	-0.002 (0.004)	-0.009 (0.004)**	-0.023 (0.053)	0.109	0.008 (0.006)	-0.004 (0.005)
Graduate on time	-0.139 (0.048)***	-0.018			-0.146 (0.028)***	-0.015			-0.128 (0.043)***	0.012		
Graduate late	-0.141 (0.068)**	0.041			-0.219 (0.032)***	0.077			-0.146 (0.048)***	0.008		
Constant	6.425 (0.081)***				6.171 (0.085)***				6.253 (0.102)***			
R-sq	0.074				0.197				0.167			
Observations	5957				3907				2249			

1) The sample excludes respondents without valid AFQT scores and attriters by age 22. The excluded category in the regression specification are with both mother and father present at age 14 and who did not graduate by age 20. Observations are weighted using the cross-section weights provided by the NLSY adjusted to account for attrition by age 22 and AFQT non-response. Standard errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant 10%

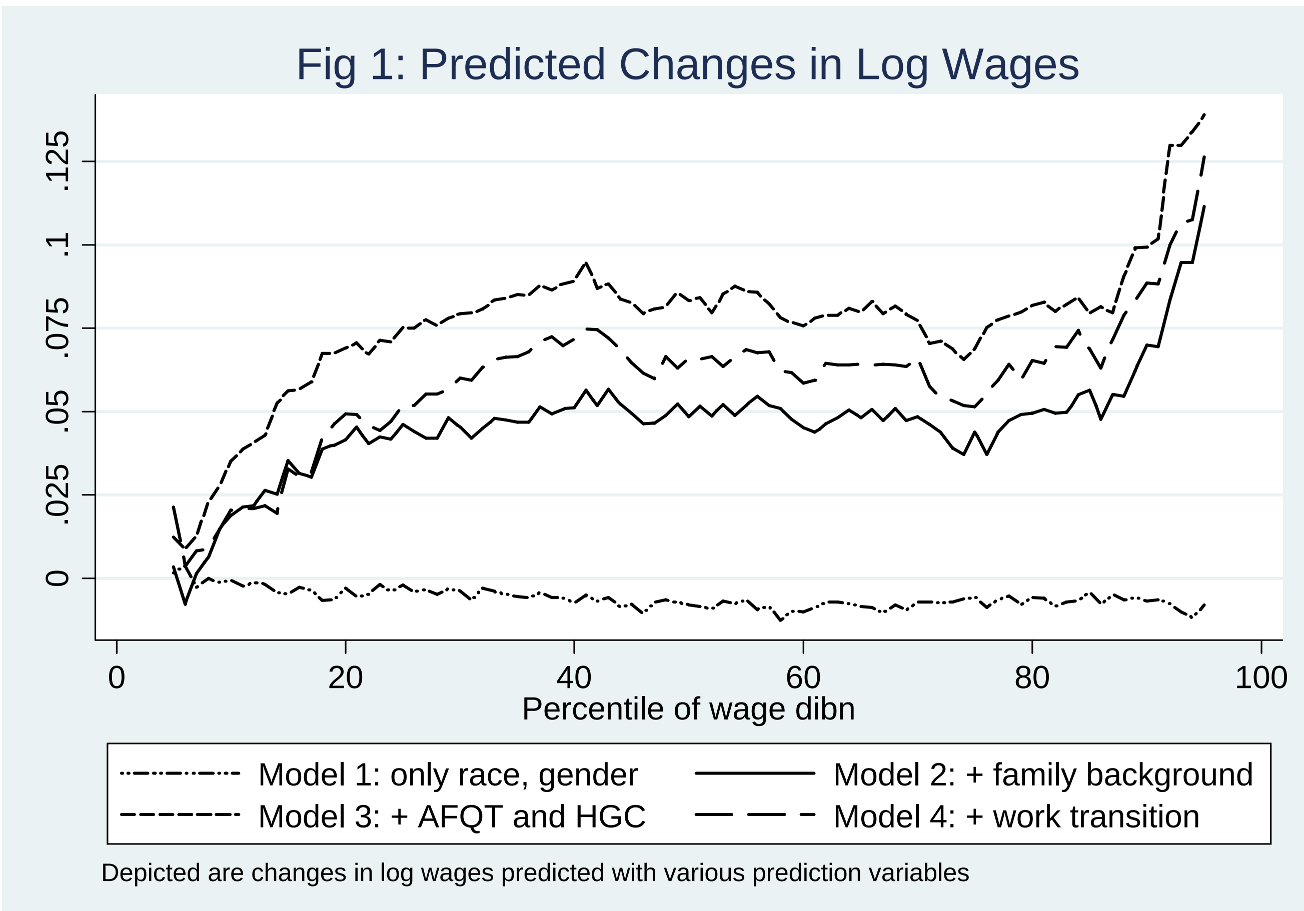


Fig 1: Predicted Changes in Log Wages
0
.025
.05
.075
.1
.125
0
20
40
60
80
100
Percentile of wage dibn
Model 1: only race, gender
Model 2: + family background
Model 3: + AFQT and HGC
Model 4: + work transition
Depicted are changes in log wages predicted with various prediction variables

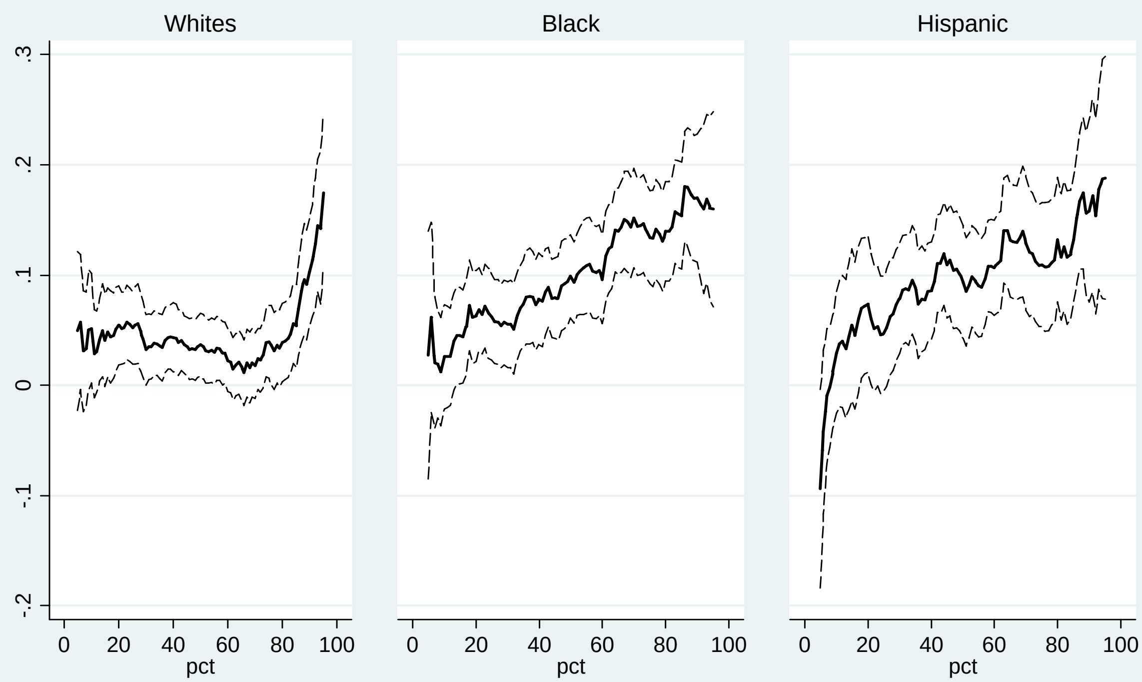


Fig 2 - 1: Predicted Change in Male Log Wages by Race

dashed lines indicate 90% coverage regions

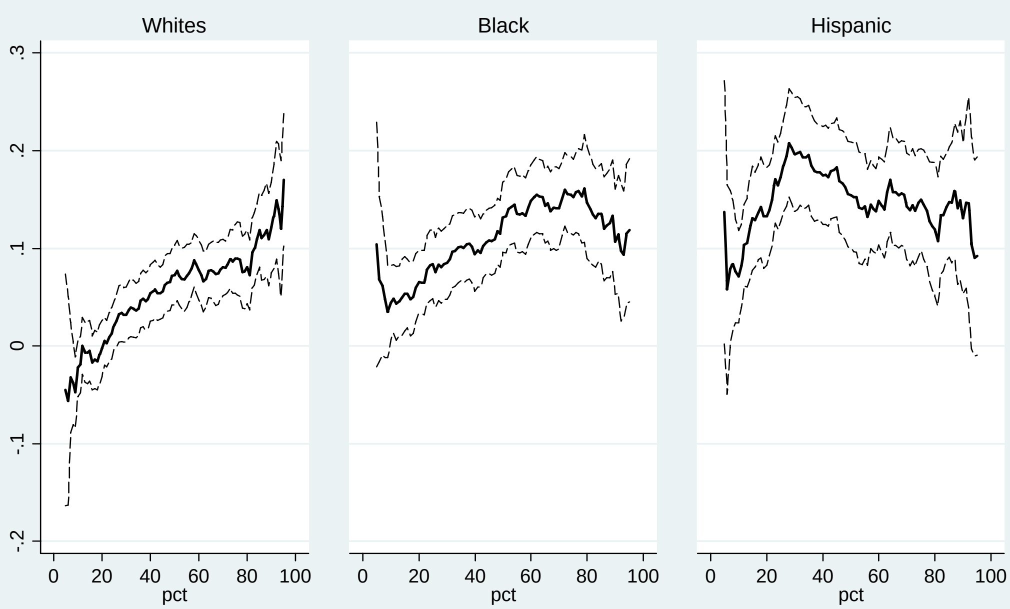
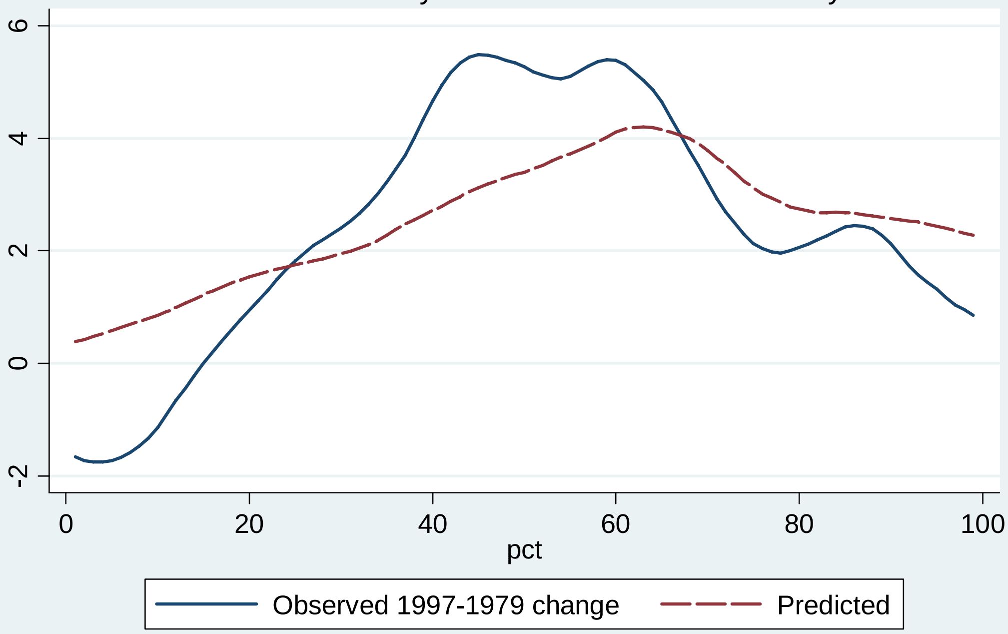


Fig 2 - 2: Predicted Change in Female Log Wages by Race

dashed lines indicate 90% coverage regions

Figure 3: Changes in the AFQT-Distribution

Observed and Predicted by Parental Education and Family Structure



Appendix Table A: EFFECTS OF SAMPLE SELECTION RULES, ATTRITION AND MISSING DATA ON SAMPLE SIZE

A. Effects of Sample Selection Rules

Reason for exclusion	**NLSY 1979** (Birthyears 1957-1964)	**NLSY 1997** (Birthyears 1980-1984)
No excluded cases	12,682	8,984
Excluded oversampled White male and female	9,757	8,984
Excluded "Other" races	9,757	8,901
Excluded if age of entry to US > 16 years	9,661	8,901
Ought to be present at age 22	**9,661**	**7,148**

B. Effects of Attrition Prior to Age 22 and Missing Data on AFQT and Education

Ought to be present at age 22	**9,661**	**7,148**
	100.00%	***100.00%***
Present at age 22	9,228	6,085
	95.52%	*85.13%*
Highest grade completed	9,201	6,014
	95.24%	*84.14%*
AFQT	8,822	4,882
	91.32%	*68.30%*

Notes: Ought to be present at age 22 is calculated using birth year information of respondents. In the 1979 cohort we expect to observe everyone at age 22. in the 1997 cohort, since the last year of interview is 2005, we only expect people born on or before 1983 to reach the age of 22 in the data. AFQT here means age-standardized AFQT. Note that a small number of cases in both cohorts are lost due to a death prior to age 22.

Appendix Table B: Testing Age Standardization of AFQT Scores							
		NLSY 1979			NLSY 1997		
		F-stat	Degrees of Freedom	P value	F-stat	Degrees of Freedom	P value
Specification 1	Cohort X Race	0.81	15, 8903	0.67	0.5	6, 5001	0.81
Specification 2	Cohort X Parental HGC	0.73	15, 7337	0.76	0.64	6, 3895	0.7
Specification 3	Cohort X HGC	0.74	8, 6824	0.65	0.82	3, 5005	0.48

Notes: Reported are test statistics from three specifcations exploring whether the relationship between the AFQT-score and observed variables changes with age of test taking. Each F-test refers to the test whether the interaction of the age of test taking with observable characteristics is 0 in a linear regression of the AFQT-score on main effects and interactions of the variable considered with age of test taking. The equipercentile matching procedure to age 16 implicitely assumes that the distribution of scores is unchanged across individuals, implying that the joint distribution of individual characteristics and test scores is the same across age. This assumption is rejected for schooling in the NLSY 1979.

Specification 1: regression of standardized afqt on cohort dummies, cohort dummies interacted with hgc, and hgc where hgc refers to highest grade

Specification 2: regression of standardized afqt on cohort and race dummies, cohort dummies interacted with race.

Specification 3: regression of standardized afqt on cohort dummies, cohort dummies interacted with hgc, cohort dummies interacted with race, cohort dummies interacted with father's hgc, hgc and mother's hgc

Appendix Table C: Parental Presence at Age 14						
Living with at age 14:		Census			NLSY79	NLSY97
		1980	1990	2000		
Social Mother and Father	Mother and Father	75.1	70.61	66.88	83.34	68.16
	Mother only	17.02	18.61	20.15	12.77	24.19
	Father only	2.44	3.44	5.06	1.39	3.74
	Neither	5.44	7.35	7.91	2.5	3.92
Biological Parents only	Mother and Father	..	..	..	75.16	52.75
	Mother only	..	..	..	18.72	35.67
	Father only	..	..	..	3	6.36
	Neither	..	..	..	3.12	5.22

Appendix Table D: The Distribution of Propensity Weights for Different Skill Models				
	Race, Sex	(1) + Family Background	(2) + AFQT, HGC	(3) + Work Transition
	Model 1	Model 2		
	(1)	(2)	(3)	(4)
Smallest	0.75	0.002	0.001	0.000
2nd Smallest	0.75	0.002	0.001	0.000
1%	0.75	0.01	0.01	0.004
5%	0.75	0.08	0.07	0.03
10%	0.75	0.16	0.15	0.05
25%	0.75	0.36	0.3	0.2
50%	0.77	0.7	0.6	0.51
75%	0.94	1.2	1.23	1.18
90%	1.66	2.14	2.14	2.26
95%	1.89	2.95	3.12	3.49
99%	1.89	6.01	6.25	7.12
2nd Largest	1.89	19.53	18.38	45.32
Largest	1.89	22.06	32.65	90.8
Mean	1	1	1	1

1) This table describes the distribution of weights used to generate the counterfactual distributions described in the paper, with the exception that the weights used in the paper are capped at a max of 10. These propensity weights are estimated on the sample with reported AFQT scores and we report the distribution of weights for a selected, representative subset of propensity models.

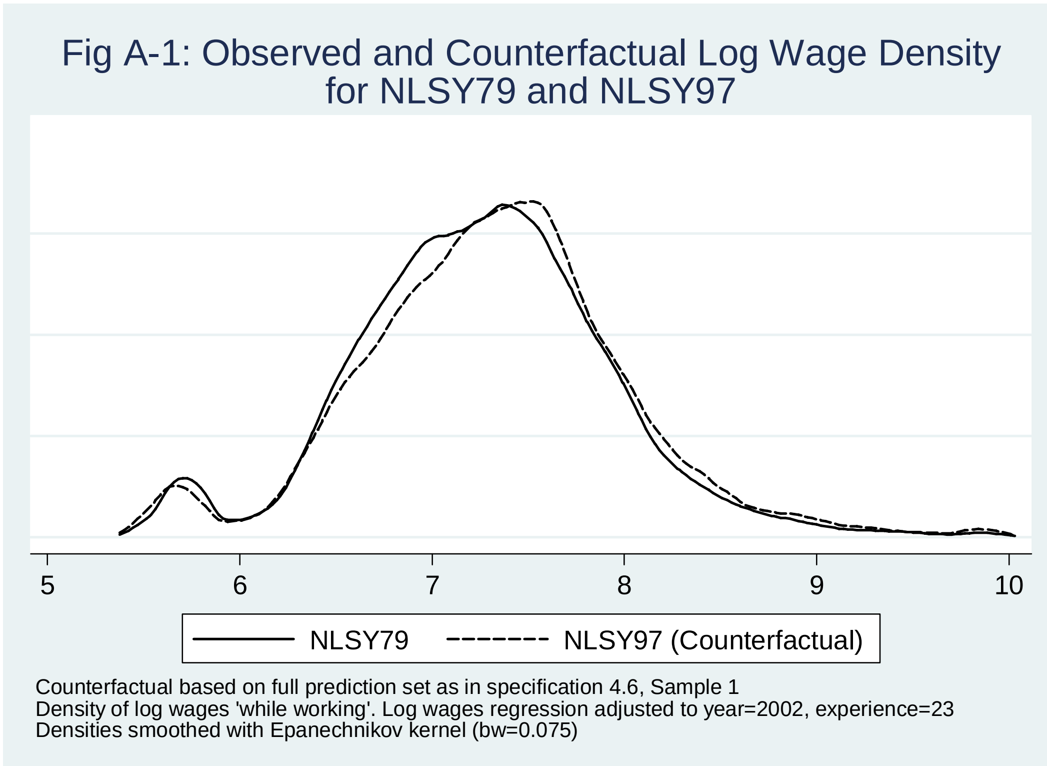


Fig A-1: Observed and Counterfactual Log Wage Density
for NLSY79 and NLSY97
5
6
7
8
9
10
NLSY79
NLSY97 (Counterfactual)
Counterfactual based on full prediction set as in specification 4.6, Sample 1
Density of log wages 'while working'. Log wages regression adjusted to year=2002, experience=23
Densities smoothed with Epanechnikov kernel (bw=0.075)

Figure A-2

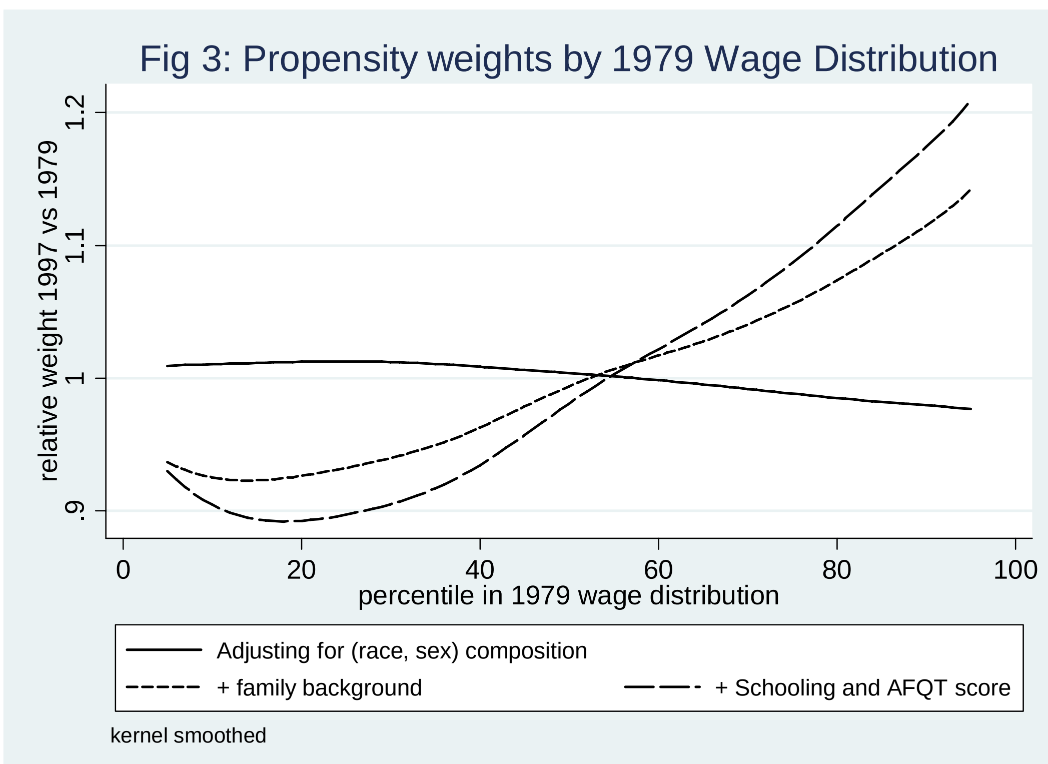


Fig 3: Propensity weights by 1979 Wage Distribution
relative weight 1997 vs 1979
.9
1
1.1
1.2
0
20
40
60
80
100
percentile in 1979 wage distribution
Adjusting for (race, sex) composition
+ family background
+ Schooling and AFQT score
kernel smoothed