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

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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. We also provide speculative estimates suggesting that if recent trends continue, the net effect of skill biased technical change and the change in the supply of human capital will be a large increase in inequality by 2025.

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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 demographic characteristics and 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

[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 find 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.

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 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 apply the density reweighting procedure introduced by Dinardo, Fortin, and Lemieux ((1995), hereafter, DFL). 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 and the wage function was unaffected. 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 decompositions based on linear regression, does not require one to specify a parametric model relating outcomes to characteristics.[5] It also allows one to examine the impact of changes in particular characteristics on statistics other than the mean. One limitation of the DFL approach is that it does not estimate parameters that relate outcomes to characteristics and that can potentially be interpreted.[6] A second limitation is that it does not permit one to identify the partial effect of a shift in

[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.

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

[5]We do not observe the adult wages of the 1997 cohort, so we cannot use DFL's procedure or a Blinder (1973) and Oaxaca's (1973) regression procedure to identify the part of the difference in the wages of the 1997 and 1979 cohort that will be due to differences in the wage functions that the two cohorts experience.

[6]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.

the marginal distribution of a variable or set of variables holding the marginal distributions of the other variables constant. We rely mainly on DFL's procedure, but also present partial effects of specific variables using multivariate regression under some strong separability assumptions that we discuss below.

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 go to great lengths to ensure that we measure our skill correlates in a consistent manner. This requires considerable data work, the details of which are described in the paper. We pay particular attention to the AFQT scores which were administered at different ages and based upon different test formats. Drawing on the work of Segall (1997), we are the first to obtain and use AFQT scores that can be directly compared across the NLSY cohorts.

Our main findings regarding the changes in skills between the 1979 and 1997 cohorts are as follows.

(1) The 1997 cohort is more advantaged than the 1979 cohort in many but not all dimensions that matter for wages. In particular, the 1997 cohort is stronger than the 1979 cohort in education, parental education, and cognitive test scores. However, the fraction of individuals who lived with both parents at age 14 declined substantially between 1979 and 1997 and individuals seem to take longer to achieve a given grade level.
(2) When we aggregate the diverse set of skill measures using adult wages we find that the skills of the younger cohort increase by about 5% for whites and more for minorities. Overall, the skill index based on adult wages indicates that young Americans today are about 6% more skilled.
(3) While skills increase across the entire distribution, the increase is significantly larger towards the top of the distribution. Skills at the 90th percentile of the distribution increase by about 9%, skills at the median by about 6% and skills at the 10th percentile by only about 1%. Overall, the skill distribution widens within race/gender groups as well as for the entire population.
(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 increase in parental education is the single most important driving force behind the changes in skill endowments. This is true for both the average skill level as for the distribution of skills. Surprisingly, most of the changes in education and cognitive test scores can be accounted for using parental education.

Even though we do observe that skills increase between the 1979 and the 1997 cohort, we find that these skill increases are relatively minor if compared to recent trends in the demand for skilled labor. Drawing on various data sources, we show that if recent trends in the growth of the demand for skilled labor persist, then the relatively slow rise in skills and the continued increase in the demand for skilled labor will lead the education premium to increase further and will contribute to substantial widening in wage inequality during the next few decades.[7] The amount depends on our assumptions, but even our low estimate suggests that the 80th/20th percentile ratio of wages might widen by about 10 log ponits. If the trends captured in Autor, Katz and Kearney (2007) persist, the ratio might widen by 30 log points.

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 the 1997 sample. In sections 6 and 7 we present our basic results. Section 8 combines our findings for the supply of skills with a forecast of the increases in the demand for skilled labor to arrive at a forecast of wage inequality in 2025. In the final section, we summarize our main findings and provide a research agenda.

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. These skill measures are 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. We choose 1998-2004 because by this time the 1979 cohort had reached the peak of its life-cycle earnings profile.[8]

Our estimates of counterfactual wage distributions answer the question, "What wages would members of the NLSY79 cohort have earned if they had the observed skills of the NLSY97 cohort and the wage function remained unchanged?". They also answer

[7]We consider only the supply of skills as a margin along which the economy can adjust to changes in the demand for skilled labor. The widening in the price of skilled labor is likely to lead to adjustment along other margins, such as outsourcing and investments into skill-saving technological research and substitutes for skilled labor.

[8]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.

the question, "What wages will members of the NLSY97 cohort earn at the peak of their life-cycle earnings in the unlikely event that they face the same wage distribution conditional on skills that the NLSY79 cohort faced?" 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 a counterfactual wage distribution based on the 1979 cohort's adult wage function and the NLSY97 cohort's skill distribution.

2.1. **Constructing the Counterfactual Wage Distribution.** Log wages in the economy faced during adulthood by the 1979 cohort are determined by $w^{79} = W^{79}(z,u)$, 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. The adult wages of the 1997 cohort will be determined by some future function $w^{97} = W^{97}(z,u)$. For each observation from the NLSY79 we obtain a realization (z, w^{79}) of the random vectors Z and W^{79}. Observations from the NLSY97 consist of realizations of Z only.

Let $g(u|z,\, 1979)$ and $g(u|z,\, 1997)$ be the conditional densities of U given Z for the 1979 and the 1997 cohorts, respectively. 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:*

$$(A.1) \qquad g(u|z,1979) = g(u|z,1997)\ .$$

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 1979 and 1997 in skill prices and 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 Appendix A we provide indirect evidence based on the link from AFQT and education to race, family background and gender. We show that the changes in race, gender, and parental background variables capture the changes in the observed distributions of AFQT and education well.

Let $f(w^{79}|1979,z) \equiv f(W^{79}(z,u)|1979,z)$ be the density of adult wages of cohort 1979 conditional on z. Let $f(w^{79}|1997,z)$ be the corresponding conditional density of $W^{79}(z,u)$ when the conditional distribution of u is that of the 1997 cohort: $g(u|z,1997)$. Assumption (A.1) implies that the conditional density of w^{79} for cohort 1979 and 1997 are the same:

$$(2.1) \qquad f(w^{79}|z,1979) = f(w^{79}|z,1997).$$

Until section 8 of the paper we always consider the 1979 wage function rather than the wage function $W^{97}(z,u)$ that the 1997 cohort will face as adults. [9]

DFL's method is as follows. Note that $f(w^{79}|1979) = \int f(w^{79}, z|1979)dz$. Equation (2.1) implies that

$$f(w^{79}|1997) = \int f(w^{79}, z|1979)\psi(z)dz \tag{2.2}$$

where

$$\psi(z) = \frac{f(z|1997)}{f(z|1979)} = \frac{p(1997|z)}{p(1979|z)}\frac{p(1979)}{p(1997)} \tag{2.3}$$

and $p(1997|z)$ and $p(1979|z) = 1 - p(1997|z)$ are the probabilities or "propensity scores" of appearing in sample 1997 and sample 1979, respectively, conditional on z. The ratio $\frac{p(1979)}{p(1997)}$ is the unconditional odds that the observation is from cohort 1979. 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 1997 conditional on z multiplied by $\frac{p(1979)}{p(1997)}$, the unconditional odds that the observation is from cohort 1979. 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 1979 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 $p(1997|z)$ 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 $f(w^{79}|\ 1997)$. In particular, we estimate $f(w^{79}|\ 1997)$ itself and compare it to $f(w^{79}|1979)$.

2.2. Measuring the Contribution of Subsets of Variables to Differences between Actual and Counterfactual 1979 Wage Distributions.

Using DFL's methodology, we can also decompose the overall difference in $f(w^{79}|1979)$ and $f(w^{79}|\ 1997)$ into the contributions of the components of the random vector Z. For simplicity, consider the case of two subvectors Z_1 and Z_2.

[9] In Section 8, we consider how the wage function faced by 1997 might differ from wages by 1979 if recent trends in skill biased technical change and the supply of skilled vs unskilled labor continue.

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

Under Assumption A.1 the distribution of w^{79} conditional on skill z are identically distributed for 1979 and 1997. Therefore,

$$\begin{aligned} f(w^{79}|1997) - f(w^{79}|1979) &= \\ \text{(2.4)} \qquad &= \int f(w^{79}|z,1979)f(z|1997)dz - \int f(w^{79}|z,1979)f(z|1979)dz \\ &\equiv \int f(w^{79}|z_1,z_2,1979)f(z_1,z_2|1997)dz - \int f(w^{79}|z_1,z_2,1979)f(z_1,z_2|1979) \end{aligned}$$

As DFL note, one may write $f(w^{79}|\ 1997) - f(w^{79}|1979)$ as

$$\begin{aligned} f(w^{79}|1997) - f(w^{79}|1979) &= \\ \text{(2.5)} \qquad &= \int f(w^{79}|z_1,z_2,1979)[(f(z_1,z_2,1997) - (f(z_2|z_1,1979)f(z_1|1997)]dz \\ &+ \int f(w^{79}|z_1,z_2,1979)[(f(z_2|z_1,1979)f(z_1|1997) - (f(z_2|z_1,1979)f(z_1|1979) \end{aligned}$$

By substitution, the above decomposition may be rewritten as

$$\begin{aligned} f(w^{79}|1997) - f(w^{79}|1979) &= \int f(w^{79}|z_1,z_2,1979)[(f(z_1,z_2,1997) - (f(z_2|z_1,1979)\psi(z_1)f(z_1|1979)]dz \\ \text{(2.6)} \qquad &+ \int f(w^{79}|z_1,z_2,1979)[(f(z_2|z_1,1979)\psi(z_1)f(z_1|1979) \\ &- (f(z_2|z_1,1979)f(z_1|1979)]dz \end{aligned}$$

where $\psi(z_1) = \frac{f(z_1|1997)}{f(z_1|1979)} = \frac{p(1997|z_1)}{p(1979|z_1)}\frac{p(1979)}{p(1997)}$. The weights $\psi(z_1)$ are estimated in exactly in the same manner as the weights $\psi(z)$ but using only the variables (z_1). The difference $f(w^{79}|\ 1997) - f(w^{79}|1979)$ can be decomposed into changes in as many subvectors $(Z_1, Z_2, ...)$ as desired.

One obtains the second term of the decomposition (2.6) by first applying $\psi(z_1)$ to the NLSY79 data to get $\int f(w^{79}|z_1,z_2,1979)[(f(z_2|z_1,1979)\psi(z_1)f(z_1|1979)dz$ and then subtracting $f(w^{79}|1979) = \int f(w^{79}|z,1979)\ f(z|1979)$. This component describes the change in the distribution of w^{79} that we would observe if the skill Z_1 was distributed as in period 1997 but the dependence between Z_2 and Z_1 remained that of 1979. For concreteness, assume that Z_1 contains the race and gender identifiers. Then, this component is the change in w^{79} that is 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 reflects the dependence between the lower order variables and race and gender that is 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) is the marginal effect of the shift in Z_2 after already accounting for the shift in Z_2 implied by the change in the distribution of Z_1.

The decomposition will depend on the order of (Z_1, Z_2) even if (i) Z_1, Z_2 and U are independent and (ii) $w^{79}(u, z_1, z_2)$ is additively separable in u, z_1 and z_2 because these conditions are not sufficient for the conditional density $f(w^{79}|z, 1979)$ to be additively separable in z_1 and z_2.[11] Since the decompositions are not unique, researchers have to take a stand. The merits of any particular ordering depends on how Z_1, Z_2, etc., are causally related. If there is no prior information about this, then the best one can do using the DFL procedure is to examine the sensitivity of the decomposition to alternative orderings. In our case there is a natural ordering to the decomposition that flows from the timing of variables. We partition the skill vector into four sub-vectors. We start by including race and gender in the propensity weight model. Second, we add parental background variables (father and mother's education and parental presence). Third, we add variables capturing individual characteristics such as education and cognitive ability scores (AFQT and HGC). 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 relationship 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. To the extent that parental education, child's education, child's test scores, and wages depend on a common factor with a distribution that is largely invariant across generations (e.g. genetic endowment), our decomposition will overstate the causal contribution of variables that are early in the sequence, such as the shift in parental education. However, Appendix A shows that the changes across cohorts in race, gender, and parental background variables do a good job of predicting the observed changes across cohorts in the AFQT and education distributions. This is reassuring, because we should overpredict the change in the AFQT and education distributions if a common factor with a cohort invariant distribution is responsible for the large role we find for parental background in the results below.

[11] The Blinder-Oaxaca decomposition of differences in means is unique even if there is dependence between Z_1 and Z_2 provided that $W^{79}(u, z_1, z_2)$ is additively separable in u, z_1, and z_2 and $g(u|z_1, z_2, z_3, t)$, $t = 1979, 1997$, is additively separable in z_1 and z_2. This result only applies to the mean and not to other statistics of $f(w^{79}|1979)$ and $f(w^{79}|1997)$.

Below, we also present standard regression decompositions of the mean of wages. These identify the partial effect of the shift in each set of variables holding the distribution of the others constant. They do not require a sequencing assumption but are valid only under strong linearity and additive separability assumptions. In addition to the decompositions into partial effects of shifts in $Z_1, Z_2, ...,$ etc., we use regression to perform a sequential decomposition into "marginal effects" that is directly analogous to the DFL composition. A major advantage of the DFL's estimator for marginal effects is that it does not require one to assume any particular form for the wage function linking skills Z and wages in $1979.$ An equally important advantage of the approach is that the decompositions based on the reweighting method apply to the entire distribution of wages and therefore all statistics of interest. The sequential decompositions into marginal effects based on the reweighting method and the regression decompositions into marginal effects and into partial effects are complimentary.

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 workplace. Nevertheless, the surveys vary sufficiently to pose challenges in making variables comparable across surveys and in ensuring that the two samples are population representative. These challenges are taken up in great detail in the Web Appendix available at [website to be determined]. In this section, we describe how we deal with those issues that we consider crucial for understanding the results that follow. We briefly discuss how we maintain a representative sample in the face of sample attrition and item non-response, and we discuss how crucial variables are constructed. We pay particular attention to how we construct a cognitive ability measure that can be compared across surveys.

3.1. **The NLSY79 and NLSY97 Samples.** We use the cross-sectional and the supplemental samples from the 1979-2004 survey years of the NLSY79 and the 1997-2006 survey years of the NLSY97 for our analysis.[12] In both surveys we construct our skill measures using all waves up to the year the individual was 22 years old. A total of 9,661 (8,901) individuals should have been observed at age 22 in NLSY79 (NLSY97) and are therefore eligible for our analysis. As we document in Web Appendix Table 1, our effective NLSY79

[12]As we discuss in the Web Appendix, MaCurdy and Vytlacil (2003) and Moore et al. (2000) examine the representativeness of NLSY97 and draw conflicting conclusions. In the paper, 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.

sample falls to 8,822 observations because we lose 4.48% of the NLSY79 observations because of attrition prior to age 22, an additional 0.28% because of missing data on highest grade completed at age 22, and an additional 3.92% because some individuals did not take the ASVAB and therefore did not take the AFQT. The NLSY97 drops to 6,131 observations due to a 14.43% loss due to attrition, an additional loss of 0.88% due to missing education, and an additional loss of 15.81% because of missing AFQT data. In the Web Data Appendix we show that attrition prior to age 22 is related to base year characteristics, but we also find only small differences between the full sample and the stayers in base year characteristics. We also show that observable characteristics such as parental education differ by availability of the AFQT score. Fortunately, given the size of these differences and the fraction of cases with missing AFQT data, the difference between the characteristics of the full sample and those with valid AFQT scores is not likely to make a big difference in our analysis.

Nevertheless, we estimate weights to adjust for attrition and missing AFQT conditional on a rich set of observables in the base-year. These weights are based on a probit model relating attrition/missing AFQT 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. We apply these weights throughout the analysis.[13]

Finally, we can check whether our results are robust to missing data on the AFQT score by analyzing a number of specifications that do not require the AFQT score by using both our main sample (hereafter: "AFQT sample") and a sample that includes those with missing AFQT scores ("Full sample"). Our results are robust to switching between these two samples.

3.2. **Variable Construction.** **Wages:** The wages of the NLSY79 cohort in the years 1998-2004. This period spans 4 survey years, since the NLSY79 moved to a biannual format

[13]A final problem arises because some of the 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 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.

in 1994. We standardize log real wages between 1998-2004 to 2002 and 23 years of potential experience.[14] We weight by the reciprocal of the number of wage observations for an individual to account for the fact that the number of wage observation differs across individuals. This implies that our wage statistics reflect the wage distribution of the population "while working".

Employment: Employment is 1 if the individual had a valid wage in the year of the survey and is 0 otherwise. We use observations from 1998-2004.

School-to-Work Transition: For those individuals who were not in school for at least two years prior to age 22, we construct a set of dummies that describe whether an individual left school before or after reaching the age of 6+highest grade completed. We also include a dummy that indicates whether the individual worked for at least 14 weeks in at least one of the first two years after leaving school.

The AFQT-Test Score: Our measure of cognitive ability, the AFQT-score, is a composite score derived from the ASVAB. The NLSY79 and 97 differ in the test format and in the age at which individuals were administered the ASVAB, and we need to account for these differences. The NLSY79 cohort took a pencil and paper (P&P) version of the ASVAB while the NLSY97 took a computer assisted test (CAT) format. The respondents to the NLSY79 were between 16 and 21 years old when they were administered the test, whereas the respondent to the NLSY97 were between 12 and 16 years old.

To achieve comparability between the two test formats we rely on a mapping between the P&P and the CAT test format provided to us by Dan Segall. 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). [15]

After first adjusting for the test format, we adjust for differences in test taking age. For the NLSY79, we perform an equipercentile mapping to age 16 of the scores of respondents who took the test at other ages. Specifically, those of age a who scored in the $q'th$ percentile among age a test takers were assigned the test score corresponding to the $q\prime th$ percentile of those who took the test at age 16. We then perform same procedure separately using the NLSY97 sample. Implicitly, we are assuming that the relative ranking of individuals in the AFQT-distribution on average does not depend on when they took the test. We also assume that the level of cognitive skills in adulthood associated with the $q\prime th$

[14]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.

[15]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 so as to match the distributions of the CAT scores. We wish to emphasize that the equipercentile mapping is based on Segall's sample—we are not imposing that the score distributions be the same for the NLSY97 and NLSY79, and in fact they are not the same. We thank Daniel Segall for providing us with the P&P equivalents of the CAT scores for the NLSY97 sample.

percentile in the age 16 test taker distribution is the same as that for the $q\prime th$ percentile in the age a distribution. We are not restricting scores across NLSY79 and NLSY97 cohorts.[16]

The construction of the other variables used in the analysis is discussed in the Web Appendix.

4. Characteristics of the 1979 and 1997 Cohorts

We can now compare how key skill indicators compare across the NLSY79 and NLSY97 cohort. As documented in Table 1, most indicators show improvement. Average education of both mothers and fathers increased substantially over this time-period. For example, mother's education rose from 11.75 to 12.71 – an increase of about 11 months. The mean of AFQT rises from 42.25 to 43.86 and highest grade completed as of age 22 increases from 12.64 to 13.0.[17]

The increases in education are not uniform across the distribution of schooling. The share of individuals with a high school diploma increased by only 1.5%-points compared with an increase of 9%-points in the share of those with more than 14 years of education. In addition, enrollment rates at age 22 are up substantially, indicating that there have been significant gains at the top of the education distribution.

These increases in cognitive test scores, education, and parental education contrast with the dramatic decline in the percentage of children who grow up in traditional family settings. In NLSY97, only 54% of 14 year olds were living with both biological parents, compared to 75.2% in NLSY79. This decline is mostly accounted for by an increase in the number of children growing up without their biological father.

Table 2 shows that the changes in skill measures are not uniform across race and gender. Parental education has increased substantially for all races, with father's education rising 1.5 years for blacks and about 1 year for whites and Hispanics. Similarly, the shares of white and black children living with both of their biological parents have declined by about 20-25%-pts. However, the share of black children in 1979 living with both their biological parents had already fallen to just over 50%. Among the NLSY97, the share of black children is down to 27% and the modal group of 14 year old black children

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[16]In the Web Appendix, we test whether the equipercentile matching of scores across ages is valid and find no evidence against our procedure.

[17]Magnuson and Waldfogel's (2008) analysis of NAEP test scores for the relevant years indicate that they move in the same direction as the AFQT scores. 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. Strictly speaking, the AFQT-test is 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.

are those living with only their biological mother. The decline in traditional family structures was less rapid among Hispanics, amongst whom the share of children living with 2 biological parents has declined by only 8%-points, from 65 to 57%.

With regard to schooling, we observe that females have gained more than males within their ethnic groups and that Hispanics have gained relative to whites and blacks. However, the gap in schooling between blacks and whites has not narrowed. Among black females, average schooling at age 22 rose by 0.5 years from 12.3 to 12.8 compared with an increase of 0.6 years among white females and 1 year among Hispanic females. Black males did not raise schooling above their 1979 level of 11.9 years, while whites and Hispanics gained 0.3 and 0.8 years respectively. However, blacks made substantial gains in the AFQT score distribution. Black females and males had very large gains in AFQT scores (8.8 and 5.6 points), while AFQT scores among white females and males rose by only by 3.1 and 1.2 points, respectively.

Overall, we observe increases in many, but not all skill measures and we observe that changes in these skill measures vary across demographic groups. We now proceed to estimate the propensity scores that allow us to aggregate these skill measures into a single skill index.

5. Estimation of Propensity Scores

Equation (2.3) shows how the propensity weights with which we reweight the data are related to the estimated propensity scores. We estimate the propensity scores using probit specifications based on the various sets of skill measures after pooling the appropriately weighted NLSY79 and NLSY97 samples. 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, and we have confirmed that the reweighted 1979 data matches the mean of skills observed in the 1997 data.[18]

[18] When we use even more flexible functional forms than Model 6 (defined below), 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. Web Appendix Table 5 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

We consider various specifications for the skill vector Z. We group the skill variables according to their 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 measures of parental education and indicators for the presence of either mother or father or both at age 14. We measure parental education using dummies for both maternal and paternal years completed. These variables 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 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.[19] Model 4 drops the AFQT terms and keeps the education terms. For the most part, our results are robust to switching the order of AFQT and schooling or including them at the same time. Our full model (Model 6), adds the variables measuring the continuity of schooling and the transition into the work-force to Model 5. We conjecture that spending time neither at work nor at school is a negative indicator for future employment and wage rates.

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 prime age years measured using the methodology and data presented in Section 2-5.

6.1. **Overall Changes in Skills.** The first result to note is that the 1997 cohort is more skilled than the 1979 cohort. Table 3 and Figure 1 shows how skills as aggregated by log

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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.

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

wages have changed across the two cohorts.[20] Bootstrap standard error are in parentheses.[21] Columns 1 and 2 of Table 3 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).[22] The bottom row of Table 3 shows that on average skills increased by about 6-7%, regardless of the specification chosen.

Figure 1 shows that skills as aggregated by wages increase by less than 3% below the 10th percentile. There is a large region between the 20th and 85th percentile where skills rose by between 5 and 6% while gains for the top decile are in the 10-15% range. This widening in the skill distribution will, all else equal, result in increased economic inequality over the next decades. Figure 1 also contains information about the contribution of various variables to the overall changes in skills. We will return to the decomposition of the total gains in more detail in Section 7.

6.1.1. *Employment.* Employment rates are less attractive than wages as a skill aggregator because they are likely to reflect differences in labor supply preferences as well as in opportunity. Nevertheless, the question of whether demographic and skill changes will lead to shifts in adult employment rates is important for the annual earnings distribution and for aggregate labor supply. For the full sample using Model 6, the characteristics of the 1997 cohort imply an employment rate decrease of only about 0.003 relative to the 1979 cohort. This is the net result of an increase of 0.001 for men and a decrease of 0.009 for women. We find more substantial increases for black men and for Hispanic men and women. For example, employment of black men will increase by 0.017.

6.2. **Race and Gender Gaps.** Overall we find that disadvantaged groups have gained relative to white males, but that at the same time the skill distribution within groups has widened. The two panels of Figure 2 present the changes in the skill distribution conditional on race and gender along with 1.65 standard error bands. The counterfactual

[20] 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. Web Appendix Figure A-1 presents the actual wage density in 1979 and the counterfactual density based on model 6.

[21] We 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 1000 times.

[22] 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.

distribution of w^{79} is obtained by reweighting to match the changing distributions of all our skill measures.

For males, we find that blacks and Hispanics gain relative to whites over most of the wage distribution. The shift in characteristics implies a reduction in the mean log wage gap between white and black men from 41 to 37 log points. The gap at the 90th percentile declines from 45 to 40 log points. 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 21 to 18 log points at the mean and from 22 to 16 log points at the 90th percentile.

In addition to the mean increase in skills of black and Hispanic males relative to whites, we also find that the skill distribution of black and Hispanic males has widened. Based on these findings we expect a significant proportion of the black and Hispanic populations to enter the middle class. In the 1979 cohort, a black (Hispanic) male at the 75th percentile of the black (Hispanic) male wage distribution is at the 47th (67th) percentile of the overall distribution of males. In the 1997 cohort, a black (Hispanic) male at the 75th percentile of the black (Hispanic) male distribution of w^{79} lies at the 60th (72nd) percentile of the distribution of w^{79} for all males in the 1997 cohort.

Figure 2.2 suggests that the skill gains of females exceed those of males. Again, Hispanics show the most dramatic gains, ranging from 10 to 20%. Likewise, black females 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 everything else equal, 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.

Overall we find that the gains of blacks and Hispanics relative to whites, and 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 skills persist. We also find that the changing distribution of skills will lead to more inequality within race and gender.

7. Decomposing the Differences between the 1979 and 1997 Skill 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.[23] First, we add

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

variables sequentially using the DFL procedure as described in section 2 and report the marginal effects of each additional group of variables across the entire distribution. Then we compare the DFL results for the mean with those obtained using regression based approaches.

7.1. **DFL Decompositions of the Entire Distribution.** Figure 1 and Table 5 show the marginal changes of the skill index as various variables are added across the entire skill distribution. 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 w^{79} of 5-6 log points over most of its distribution. At the mean, we find that the changes in the parental background variable imply a change in skills of 5.7 log points. Adding all other variables to the skill set results in an additional change in log wages that is typically below 1 log point. At the mean it contributes 0.7 log points to the change in the skill index. 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 three quarters 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, the other skill measures have only improved by small amounts, if at all.

Columns 3 and 4 of Table 5 separately report the marginal effects of AFQT and schooling. The marginal effect of adding AFQT is zero across the entire distribution. Adding schooling (column 4) has a fairly sizable effect of 1.7 log points at the mean and 0.4, 2.2, and 2.1 at the 10th, 50th, and 90th quantiles respectively. The school to work transition variables (column 7) have a small negative marginal effect on the w^{79} distribution for the 1997 cohort. 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.[24]

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 clear case for first introducing race and sex followed by parental background before adding AFQT or education outcomes. However, the AFQT and school outcomes are jointly determined, so it is far from obvious

[24]Web Appendix Figure A-2 provides a different take on the shifts in various skill indicators. Each datapoint 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 reweighting 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.

that causal priority should be given to the AFQT. In column (5) and (6) of Table 5, we switch the order and add HGC first. Reversing the order does not alter 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, column 6 reports that once schooling has been accounted for, the marginal effect of the AFQT is negative at the mean.

Table 6 breaks down the marginal effects on the mean for each race/sex group.[25] The results show much larger effects of parental background for Hispanics than for whites and blacks, as we discuss in more detail below. Note also that for black males the improvement in AFQT is 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.

Overall, we find that the family background variables and in particular parental education are the crucial variables in determining the change in the skill distribution between NLSY79 and NLSY97. For the entire population, both the mean change and the change in the distribution of skills is largely explained by the changing distribution of parental education. Changes in other variables, namely AFQT, are important for explaining changes in the skills of some subgroups, such as blacks, but even for blacks, parental education is the main driving variable. The caveat that common factors that influence several of our skill correlates will lead to an overstatement of the importance of the parental background shift bears repeating, however.

7.2. **Regression decompositions.** In this section we provide regression decompositions of the mean and compare them to the DFL based decompositions. We learn from these comparisons what role nonlinearity in the wage function and dependencies among the variables play in generating the overall shift in wages. 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) $W^{79}(u, z_1, z_2, .., z_K)$ is additively separable in z_1, z_2, z_K and the function $\varepsilon(u)$,

(A.3) $W^{79}(u, z_1, z_2, .., z_K)$ is linear in z with slope coefficients,

[25]Decompositions by race and gender for the entire distribution are presented in the Web Appendix (Table 6).

(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) $E(Z_k|z_1, .., z_{k-1}, 1979) = \pi_{k0}^{1979} + z_1\pi_{k1}^{1979} + z_2\pi_{k2}^{1979} + ... + z_{k-1}\pi_{kk-1}^{1979}$ where $\pi_{kk'}^{1979}$ are coefficient matrices conformable to z_k and $z_{k'}$.

Assumptions A.1-A.4 imply

$$E(W^{79}|z, 1979) = \beta_0 + z_1\beta_1 + z_2\beta_2 +, .., z_K\beta_K.$$

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 Z_k is $[E(Z_k|\ 1997) - E(Z_k|1979)]\beta_k$. 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.[26]

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 $\tilde{Z}_k = Z_k - (\pi_{k0}^{1979} + Z_1\pi_{k1}^{1979} + Z_2\pi_{k2}^{1979} + ... + Z_{k-1}\pi_{kk-1}^{1979})$ for $k > 1$. One may rewrite $E(Z_k|z_1, .., z_{k-1}, 1979)$ as $(\gamma_{k,0}^{1979} + z_1\gamma_{k1}^{1979} + \tilde{z}_2\gamma_{k2}^{1979} + ... + \tilde{z}_{k-1}\gamma_{kk-1}^{1979})$, where γ_{kj}^{1979} is a function of the $\pi_{k',k''}^{1979}$, $k \geq k' > j$; $k \geq k'' \geq j$.[27]

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

$$[E(Z_1|1997) - E(Z_1|1979)]\beta_1 + \sum_{\ell=2}^{K}[E(Z_1|1997) - E(Z_1|1979)]\gamma_{\ell,1}^{1979}\beta_\ell.$$

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:

$$[E(\tilde{Z}_k|1997) - E(\tilde{Z}_k|1979)]\beta_k + \sum_{\ell=k+1}^{K}[E(\tilde{Z}_k|1997) - E(\tilde{Z}_k|1979)]\gamma_{\ell,k}^{1979}\beta_\ell.$$

For each $\ell > k$ we estimate the γ_{lk}^{1979} 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 for the entire population.[28] The first is the marginal effect based on the DFL decomposition and the second is the marginal effect based on the regression decomposition. These

[26] 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.

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

[28] A more detailed analysis of results by race and gender is available in Altonji, Bharadwaj, and Lange (2008).

are alternative estimates of the same parameter if A.2-A.5 hold. We also estimate the partial effect from the regression decomposition.

Table 7 displays the three effects for the full population. 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 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. The marginal effect 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 subsequent rows of the table weighted by the multiple regression coefficients from column 1. The order in which groups of variables are added when computing marginal effects is the same as the order of the rows. The order corresponds to Table 5 with AFQT entered before HGC, 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 and from DFL do differ somewhat. Overall, the regression decomposition implies a mean log wage increase of 0.042, 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. They are particularly important for parental education and family structure. The partial effect of the increase in parental education is 0.019 and the shift away from 2 parent families implies a partial effect of -0.007. These estimated partial effects hold HGC, AFQT, and the school to work transition constant as family background varies. Combining these estimates implies that the partial effect of the shift in parental background is only 0.012. 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 7 indicate that the marginal effect of the changes in parental background variables is to increase skills by about 5-6%.

Based on 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 0.022, the sum of the partial effects. The marginal 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 7, 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 1.6 points.

Overall, both the regression and DFL decompositions underline the important role of parental education for understanding the evolution of skills (aggregated through the w^{79} metric) 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 of the increase in skills can be explained by the direct and indirect effects of the shift in parental education on wages.

8. Wages in 2025

So far we have shown how the distribution of skills changed between the NLSY79 and the NLSY97 cohort using the wage function $W^{79}(z, u)$ faced by the 1979 cohort to aggregate skills. In this Section, we go out on a limb and provide a range of forecasts of the adult wage distribution of the NLSY97 for the year 2025.[29] To arrive at these estimates, we predict the demand and the supply of skills in 2025, which jointly determine the predicted distribution of earnings.

Our results suggest that earnings inequality for the NLSY97 will be substantially larger than for the NLSY79 cohort. Three broad trends drive the increase. First, we have already shown that the supply of skills is more unequal among today's young adults.

[29]Space limitations force us to only sketch how we arrive at these estimates. Details are available from the authors upon request. Edwards and Lange (in progress) provides a more complete analysis.

Second, based on trends observed in the US economy during the last 40 years, we predict that skill biased technical change (SBTC) will continue to increase the relative demand for educated labor. Third, our analysis of the NLSY97 and NLSY79 along with data from the CPS and Census suggests that the gap in skills between cohorts entering and exiting the labor force is narrowing. This implies that the growth in the supply of college type human capital will slow down substantially during the next two decades.

We follow Katz and Murphy (1992) and conceptualize the demand for skills using a CES production with two labor inputs: High School and College efficiency units of human capital.[30] This production function is subject to technical change that favors the demand for college type human capital. Katz and Murphy (1992) specify this rate of technical change to be constant. The Katz and Murphy (1992) specification has the great advantage of parsimony; the constant elasticity of substitution and the constant rate of technological change fully describe the relative demand for skills over time.

In order to estimate the elasticity of substitution and the rate of SBTC, we need to construct a time-series of human capital rental rates and quantity series for both high school and college human capital. We rely on CPS data from 1973-2007, using Heckman, Lochner and Taber's (1998) "flat spot" method. Between ages 45-55, life-cycle earnings profiles are flat, indicating that human capital accumulation has ceased. Since human capital is constant for cohorts in this age range, changes in wages across years will be due to human capital rental rates. Consequently, we can use within-cohort changes in wages across-years for those cohorts between 45-55 to back out a time-series of human capital rental rates. This time-series is not confounded by differential patterns of human capital accumulation across cohorts. With a time-series of rental rates in hand, we can also estimate the human capital supplied by different cohorts in different years by dividing observed earnings by the rental rate of human capital and then sum across cohorts to obtain the aggregate supply of human capital.[31] We use the time-series of human capital rental rates and quantities to estimate the crucial parameters of the Katz and Murphy (1992) framework: the elasticity of substitution and the rate of skill-biased technical change (SBTC).

Using data from 1973-2007, we find an elasticity of substitution of about 6 and an annual rate of SBTC of 1%. Our estimates differ somewhat from others in the literature

[30]We follow the literature in how we treat high school drop-outs, those with some college, and those with more than 16 years of education. High school drop-outs are assumed to be perfect substitutes for high school graduates. Similarly, those with more than 16 years of education are assumed to be perfect substitutes for college graduates. Finally, while those with some college are assumed to provide equal shares of high school and college human capital.

[31]Note that our approach allows for possibility that the mean and distribution of human capital within the high school and college categories differs across cohorts. This is broadly consistent with our use above of multiple skill indicators such as parental education and AFQT in addition to an individual's education.

based on a similar methodology. Katz and Murphy (1992) used data from the 1963-1987 CPS and found an elasticity of substitution of about 1.5 with a rate of SBTC of 2.2%. More recently, Autor, Katz, and Kearney (2008) (hereafter: AKK) provide updated estimates using data from 1963 to 2005 and report elasticities of substitution of about 2 and a rate of SBTC between 2 and 2.5%.[32]

The fact that the parameter estimates vary with the particular time-period used reflects the fact that all of them are based on relatively short time-series of wages and quantities. (Our use of the "flat spot" method plays only a minor role.) They are also based on strong assumptions about the structure of the economy, and these are necessary to use the estimates to make out-of-sample predictions. Since there is considerable uncertainty surrounding the demand parameters, we report forecasts using 4 different sets of parameter values for the elasticity of substitution and the rate of SBTC. The "high" scenario combines our projections of the changes in the supply of college and high school human capital described below with a projection for the relative demand for college and high school human capital based on AKK. To be precise, the high scenario imposes an elasticity of substitution between college and high school human capital of 2 and a rate of SBTC of 2.25% similar to the estimates reported by AKK. The "medium" scenario is based on our own estimates and imposes a high elasticity of substitution of 6 as well as a rate of technical change of 1%. Finally, the "low" scenario imposes the relatively low elasticity of substitution of 2 from AKK and the low rate of SBTC of 1% that we obtain. Under this scenario, increases in the supply of college vs. high school human capital have large effects on relative wages and the rate of SBTC is low. The low scenario therefore stacks the deck against predicting that wage inequality will increase substantially in the next decades. In addition, we report a "base" scenario that assumes that relative rental rates will stay unchanged between 2002 and 2025. Since this specification assumes that $W^{97}(z,u)$ will be the same as $W^{79}(z,u)$ up to a trend affecting all skill types identically, the results are identical to line 4 in Figure 1. We simply relabel it as a prediction for the wage distribution of the 1997 cohort in 2025.

Having specified the demand side of the economy, we now estimate the supplies of high school and college type human capital for all years up to 2025. We draw on the

[32]It is noteworthy, that our estimates are quite different from the standard estimates in the literature. The difference between our results and those reported by AKK is most likely a result of the different time-period we are examining. Estimates of the elasticity of substitution between college and high school types of human capital using aggregate time-series data are sensitive to excluding the 1960s and early 1970s. Much of the variation in the supply of college relative to high school skilled labor that identifies the elasticity of substitution in Katz and Murphy (1992) and AKK comes from the constrat between relative wage changes during the 1970s, when the supply of college type labor grew rapidly, with the changes in wages during the 1960s when the supply of college type labor grew much less rapidly. Our current data extends back only to 1973 and thus lacks this useful variation in the supply of skills. We are working to extend our data back to 1963.

1973-2007 May/MORG CPS data to forecast how the human capital supplied by cohorts born prior to 1980 will evolve up to 2025. Using the time-series of rental rates obtained from the flat-spot method, we can back out how much human capital different cohorts supplied up to 2007. To forecast the supply of human capital by cohorts born after 1980 we draw on our estimates of the change in the supply of skills obtained from the NLSY. This provides an estimate of the change in human capital conditional on education between the 1957-1964 and the 1980-1984 cohorts. For cohorts born after 1980-84, we linearly extrapolate the skill trend.[33] Finally, we draw on data from Vital Statistics, the CPS and the 2000 Census to account for mortality, changing cohort sizes and variation in labor supply and earnings profiles over the life-cycle. Together, this data allows us to estimate the total stock of human capital of college and high school type of labor up to 2025.

We combine these estimates of the supply and demand of different types of human capital to generate projections of how the rental rates of human capital will evolve between today and 2025. Figure 3 shows both the observed and our predicted relative prices (based on the medium scenario) and quantities for the 1973-2025 period.[34] During the 1980s, the supply of college human capital increased rapidly, but this increase has progressively slowed. We predict that it will come to a virtual halt in the next decades. This slow-down in the growth rate of college to high school human capital is driven by a convergence in the relative education levels between those cohorts that are entering relative to those that are retiring from the labor force. This fact, and the fact that the quantity of human capital *conditional* on education levels has not changed much over the last 30 years implies the concave shape in the supply of college relative to high school human capital. Figure 3 also shows that the upward pressure on relative rental rates for college and high school human capital will continue during the next 2 decades. Based on the recent trends in the supply and demand for educated labor, we expect relative wages of college to high school labor to increase substantially, although the amount depends on the scenario.

We next apply these changes in the relative price of college versus high school human capital to the estimate of the skill distribution of NLSY97 relative to NLSY79 that underlies line 1 in Figure 1. For this purpose, we apply the change in the relative prices of college to high school human capital from 2000 to 2025 obtained in this section to the skill distribution of the NLSY97 cohort (measured in w^{79} units). This amounts to multiplying the wages of those with some college and those with college or more by the factors implied by the changes in the relative rental rates. This delivers a forecast of

[33]That is, we predict that high school graduates born after 1984 will have endowments of high school human capital equal to that of the 1980-84 cohorts plus an adjustment that allows for the continuation in the cohort trend between the 1957-64 and the 1980-84 cohorts.

[34]The price measures are log differences in the rental rate for college and high school human capital. The difference in the observed rental rates is normalized to zero in 1973. The quantity measure is the log ratio of College to High School efficiency units of human capital.

the change in the wage distribution. Figure 4 shows these changes in the relative wage distribution normalized to 0 at the median wage for the 4 scenarios discussed above. The high scenario based on AKK's estimates implies an increase in the relative rental rates for college human capital between 2002 and 2025 of 47%. The medium scenario based on our estimates predicts that the relative rental rates will rise by 25% while the low scenario predicts that relative rental rates will increase by 16%. These increase in the relative rental rates are large by any standard. The much commented upon increase in college to high school wages during the 1980s and 1990s for instance amounted to an increase in the relative rental rates of about 12%.

This increase in the relative rental rates for college and high school human capital combined with the widening in the skill distribution predicts significant widening in the wage distribution. If we project relative rental rates to grow as implied by the AKK parameter estimates, then we forecast that the P80/P20 difference in log wages for this cohort will increase by about 30 log points relative to the NLSY79 cohort. Almost the entire increase is due to the increase in the rental rate for college vs. high school human capital rather than the widening in the dispersion of skills. Clearly, this extremely large increase in inequality is driven by the assumption that SBTC will continue at a high rate consistent with the evidence documented in AKK. However, we might expect SBTC to slow down[35], especially if R&D is endogenous and will thus be increasingly targeted towards replacing expensive, highly skilled labor. Labor market institutions may also change.

However, even if SBTC slows down considerably, say to 1% per year as in the medium scenario and low scenarios, we still project large increases in inequality. Under the low scenario shown in Figure 4, P80/P20 ratio increases by about 10% and the P90/P10 ratio increases by about 15%. This widening in the earnings inequality is driven by continued and relatively slow SBTC as well as by the slow-down in acquisition of skills and the widening in the skill distribution documented earlier in this paper.

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

[35]Indeed AKK report results that since 1992 SBTC might have slowed down by between 0.5-1% to proceed at a still fast pace of about 1.5%.

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.

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 the change seems to be generated by changes in the distribution of parental education. That is, we find 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, subject to the caveat concerning common factors. 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 substantially relative to men. Significant skill gaps remain, but blacks and Hispanics have narrowed the gap in skills relative to whites.

We also provide some speculative estimates that show that skill biased technical change and the relatively small increase in the supply of skilled labor will generate substantial pressure towards increased wage inequality and further increases in the education premium. Clearly, the supply of skills is not the only margin along which the economy can adjust to the increased demand for skilled labor. For example, we might expect that firms will invest more heavily into capital and technologies that can substitute for skilled labor. We might also expect that the US economy will observe significant outsourcing of skilled jobs in the next few decades. However, the estimates provided here show that the projected increase in the demand for skilled labor will not be met by a nearly equal increase in the supply of skilled labor. In the language of Goldin and Katz' (2008), skills seem to be losing the race against technology.

There is a substantial research agenda. 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.

In future work, we hope to extend the methods used in this paper 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.

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11. Appendix A: 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 on 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. Appendix Figure 1 compares the observed with the predicted changes in the AFQT distribution. The solid line shows how the observed AFQT score changed across the distribution.[36] The dashed line shows the predicted changes based on 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.

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

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

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.[37]

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 and 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 interactions with the 1997 indicators show whether the conditional mean of AFQT varies differentially with other skill measures across cohorts. None of the interaction terms are individually significant at the .25 level, and the variables are jointly insignificant.[38] 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.

[37]

	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

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

Table 1 Summary Statistics

Variable	1979	1997	Difference (1997-1979)
AFQT	42.25	43.86	1.61 (0.44)***
HGC at age 22	12.64	13.00	0.36 (0.03)***
GED at age 22	5.81%	6.96%	1.15 (0.38)***
HS Diploma at age 22	78.61%	80.10%	1.49 (0.63)**
HGC>=14 at age 22	31.24%	40.04%	8.80 (0.74)***
Enrolled at age 22	20.30%	29.13%	8.83 (0.67)***
Father's HGC	12.06	12.73	0.68 (0.05)***
Mother's HGC	11.75	12.71	0.95 (0.04)***
Mother only	18.52%	35.37%	16.85 (0.65)***
Father only	3.00%	5.61%	2.60 (0.30)***
Mother and Father	75.24%	54.05%	-21.19 (0.69)***
Neither Mother nor Father	3.23%	4.96%	1.73 (0.29)***
Work after leaving school	83.11%	84.15%	1.03 (0.86)
Sample size for variables measured at age 22	9228	7617	
Overall sample size	9661	8901	

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). Difference statistically significant at the .01 level (***), .05 level (**) or .10 level (*). Std errors reported in parenthesis.

Table 2: Summary Statistics by Race and Gender

Both Genders	White			Black			Hispanic		
	1979	1997	Difference (1997-1979)	1979	1997	Difference (1997-1979)	1979	1997	Difference (1997-1979)
Father's HGC	12.45	13.32	0.87 (0.07)***	10.6	12.21	1.61 (0.08)***	9.58	10.42	0.83 (0.14)***
Mother's HGC	12.11	13.24	1.13 (0.05)***	10.99	12.48	1.49 (0.07)***	9.07	10.58	1.50 (0.12)***
Mother only	14.21%	30.28%	16.53 (0.90)***	38.08%	57.88%	19.71 (1.41)***	26.87%	34.02%	7.64 (1.70)***
Father only	3.11%	6.20%	3.10 (0.46)***	2.66%	4.69%	2.05 (0.54)***	2.44%	3.96%	1.44 (0.66)***
Mother and Father	80.65%	59.41%	-21.35 (0.98)***	50.28%	27.61%	-23.02 (1.36)***	65.67%	58.39%	-7.63 (1.78)***
Neither Mother nor Father	2.02%	4.10%	2.55 (0.40)***	8.98%	9.82%	1.40 (0.90)**	5.02%	3.62%	-0.58 (0.74)

Males	White			Black			Hispanic		
	1979	1997	Difference (1997-1979)	1979	1997	Difference (1997-1979)	1979	1997	Difference (1997-1979)
AFQT	48.52	49.72	1.19 (0.86)	17.91	23.11	5.20 (0.84)***	27.67	32.09	4.42 (1.26)***
HGC at age 22	12.74	13.05	0.32 (0.06)***	11.9	11.94	0.04 (0.08)	11.71	12.47	0.77 (0.10)***
GED at age 22	5.84%	8.04%	2.20 (0.79)***	8.09%	11.33%	3.24 (1.21)***	8.87%	5.57%	-3.31 (1.32)**
HS Diploma at age 22	79.94%	81.67%	1.73 (1.24)	64.66%	61.89%	-2.78 (1.97)	60.18%	77.62%	17.44 (2.34)***
HGC>=14 at age 22	33.15%	40.47%	7.33 (1.62)***	18.56%	20.30%	1.74 (1.62)	18.70%	25.80%	7.10 (2.26)***
Enrolled at age 22	24.34%	30.38%	6.04 (1.51)***	13.29%	16.24%	2.96 (1.45)**	15.62%	25.73%	10.10 (2.22)***

Females	White			Black			Hispanic		
	1979	1997	Difference (1997-1979)	1979	1997	Difference (1997-1979)	1979	1997	Difference (1997-1979)
AFQT	47.51	50.6	3.09 (0.81)***	18.87	27.66	8.79 (0.79)***	24.52	32.08	7.56 (1.13)***
HGC at age 22	12.89	13.51	0.62 (0.07)***	12.33	12.75	0.42 (0.08)***	11.71	12.68	0.97 (0.10)***
GED at age 22	5.18%	5.51%	0.33 (0.71)	5.47%	6.49%	1.03 (0.95)	5.58%	5.32%	-0.27 (1.14)
HS Diploma at age 22	83.48%	84.88%	1.41 (1.17)	73.80%	77.31%	3.51 (1.73)**	64.32%	78.74%	14.42 (2.20)***
HGC>=14 at age 22	34.82%	51.86%	17.03 (1.55)***	25.30%	33.45%	8.14 (1.83)***	19.00%	33.36%	14.36 (2.24)***
Enrolled at age 22	19.05%	34.12%	15.07 (1.36)***	16.29%	25.40%	9.11 (1.62)***	15.42%	24.08%	8.66 (2.04)***

Notes: See Table 1. The 1997 data contains an additional race category "others". We exclude this category due to its small size and due to the fact that it is absent in 1979.

Table 3: 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 (0.029)	6.229 (0.03)	0.012 (0.031)	0.009 (0.030)	-0.001 (0.033)	0.001 (0.032)
10%	6.491 (0.011)	6.488 (0.011)	0.011 (0.015)	0.028 (0.013)**	0.027 (0.013)**	0.021 (0.013)
25%	6.844 (0.009)	6.841 (0.008)	0.045 (0.013)***	0.071 (0.011)***	0.07 (0.011)***	0.061 (0.011)***
50%	7.268 (0.009)	7.266 (0.009)	0.058 (0.013)***	0.078 (0.011)***	0.078 (0.011)***	0.072 (0.011)***
75%	7.664 (0.009)	7.663 (0.008)	0.05 (0.013)***	0.07 (0.014)***	0.064 (0.013)***	0.060 (0.013)***
90%	8.040 (0.014)	8.039 (0.014)	0.086 (0.020)***	0.100 (0.021)***	0.093 (0.020)***	0.092 (0.02)***
95%	8.328 (0.022)	8.325 (0.022)	0.127 (0.030)***	0.141 (0.031)***	0.135 (0.030)***	0.132 (0.03)***
Mean	7.264 (0.008)	7.262 (0.008)	0.056 (0.011)***	0.075 (0.01)***	0.072 (0.01)***	0.066 (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 1000 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 4: Changes in Skill by Race and Gender

Percentile	Males			Females		
	White	*Black*	*Hispanic*	*White*	*Black*	*Hispanic*
10%	0.050 (0.027)*	-0.016 (0.041)	0.025 (0.044)	-0.026 (0.038)	0.043 (0.039)	0.065 (0.047)
50%	0.034 (0.018)*	0.070 (0.039)	0.089 (0.037)**	0.065 (0.029)**	0.123 (0.041)***	0.155 (0.036)***
90%	0.108 (0.048)**	0.169 (0.056)***	0.156 (0.08)*	0.117 (0.036)***	0.104 (0.043)**	0.135 (0.061)**
Mean	0.051 (0.021)*	0.072 (0.031)**	0.082 (0.035)**	0.051 (0.019)***	0.104 (0.027)***	0.132 (0.031)***

Notes: See Table 3.

Table 5: Identifying the Contribution of Subsets of Variables to Differences between the 1979 and 1997 Wage Distributions

Percentile	Marginal Effects of Additional Variables							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Grade Completed					
	Race, Sex	(1) + Family Backgrnd.	(2) + AFQT	(3) + Highest Grade	(2) + Highest Grade	(5) + AFQT	(6) + Work Transition	Combined Effect of All Variables
	Model 1	Model 2	Model 3	Model 5	Model 4	Model 5	Model 6	Model 6
5%	0.001 (0.007)	0.002 (0.027)	0.002 (0.006)	-0.004 (0.015)	0.006 (0.013)	-0.009 (0.008)	0.011 (0.016)	0.012 (0.046)
10%	-0.005 (0.003)	0.021 (0.012)*	0.001 (0.003)	0.004 (0.006)	0.012 (0.006)**	-0.007 (0.005)	-0.010 (0.009)	0.011 (0.02)
25%	-0.005 (0.003)	0.050 (0.009)***	0.000 (0.004)	0.016 (0.005)***	0.026 (0.006)***	-0.010 (0.004)**	-0.016 (0.008)**	0.045 (0.016)**
50%	-0.01 (0.003)***	0.058 (0.010)***	0.002 (0.004)	0.022 (0.005)***	0.030 (0.006)***	-0.007 (0.004)*	-0.014 (0.007)**	0.058 (0.016)***
75%	-0.007 (0.003)**	0.053 (0.009)***	-0.001 (0.004)	0.015 (0.007)**	0.024 (0.008)***	-0.010 (0.005)**	-0.010 (0.006)*	0.050 (0.016)***
90%	-0.009 (0.003)***	0.080 (0.017)***	0.000 (0.007)	0.021 (0.009)***	0.029 (0.011)***	-0.008 (0.006)	-0.006 (0.007)	0.086 (0.027)***
95%	-0.010 (0.005)**	0.124 (0.030)***	-0.002 (0.011)	0.020 (0.012)	0.027 (0.015)*	-0.009 (0.009)	-0.005 (0.011)	0.127 (0.042)***
Mean	-0.008 (0.002)***	0.057 (0.009)***	0.000 (0.004)	0.017 (0.004)***	0.026 (0.005)***	-0.009 (0.003)***	-0.010 (0.005)**	0.056 (0.014)***

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 1000 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. Each column shows the incremental contribution of relevant variables in the title of each column.

Table 6: Identifying the Contribution of Subsets of Variables by Race and Gender

		Marginal Effect on Mean Wages						
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Alternative Orderings of AFQT and Highest Grade Completed					
		Family Backgrnd.	(1) + AFQT	(2) + Highest Grade	(1) + Highest Grade	(4) + AFQT	(5) + Work Transition	Combined Effect of All Variables
		Model 2	Model 3	Model 5	Model 4	Model 5	Model 6	Model 6
Male	*White*	0.057 (0.018)***	-0.016 (0.008)**	0.017 (0.006)***	0.018 (0.008)**	-0.017 (0.006)***	-0.006 (0.009)	0.051 (0.021)*
	Black	0.053 (0.022)**	0.018 (0.013)	0.001 (0.011)	0.003 (0.012)	0.016 (0.014)	-0.004 (0.014)	0.072 (0.031)**
	Hispanic	0.102 (0.028)***	0.001 (0.013)	0.002 (0.011)	0.019 (0.012)	-0.016 (0.012)	-0.023 (0.014)	0.082 (0.035)**
Female	*White*	0.043 (0.015)***	0.000 (0.004)	0.024 (0.009)***	0.035 (0.009)***	-0.011 (0.005)***	-0.015 (0.008)*	0.051 (0.019)***
	Black	0.060 (0.018)***	0.043 (0.016)**	0.005 (0.006)	0.026 (0.01)***	0.022 (0.014)	-0.002 (0.011)	0.104 (0.027)***
	Hispanic	0.087 (0.022)***	0.025 (0.013)*	0.021 (0.012)*	0.047 (0.015)***	-0.001 (0.011)	0.001 (0.013)	0.134 (0.031)***

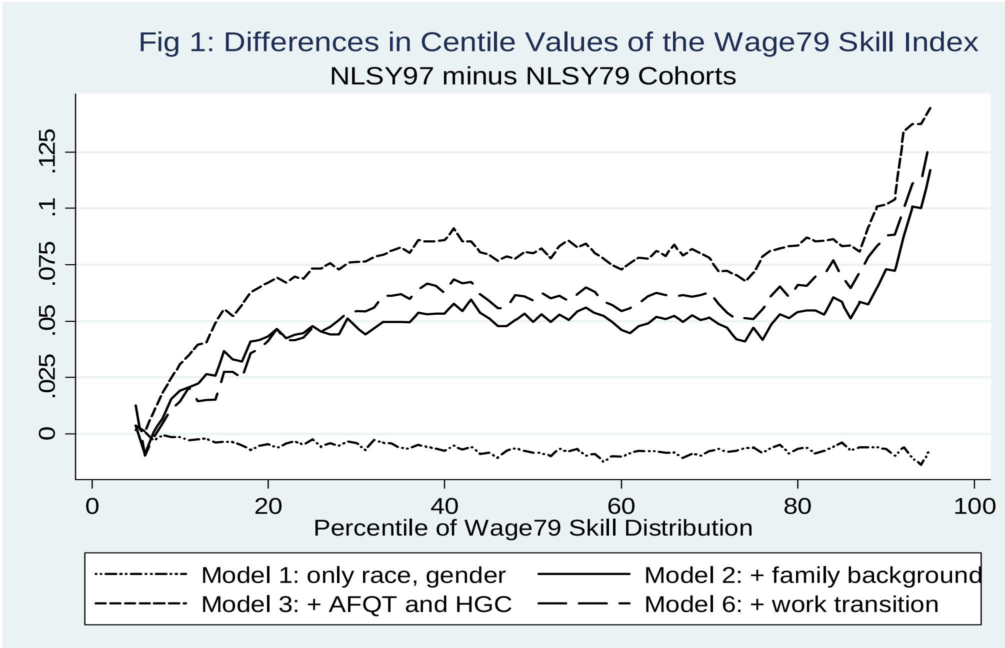
Notes: See Table 5.

Table 7: Regression Decompositions, All Groups Combined[1]

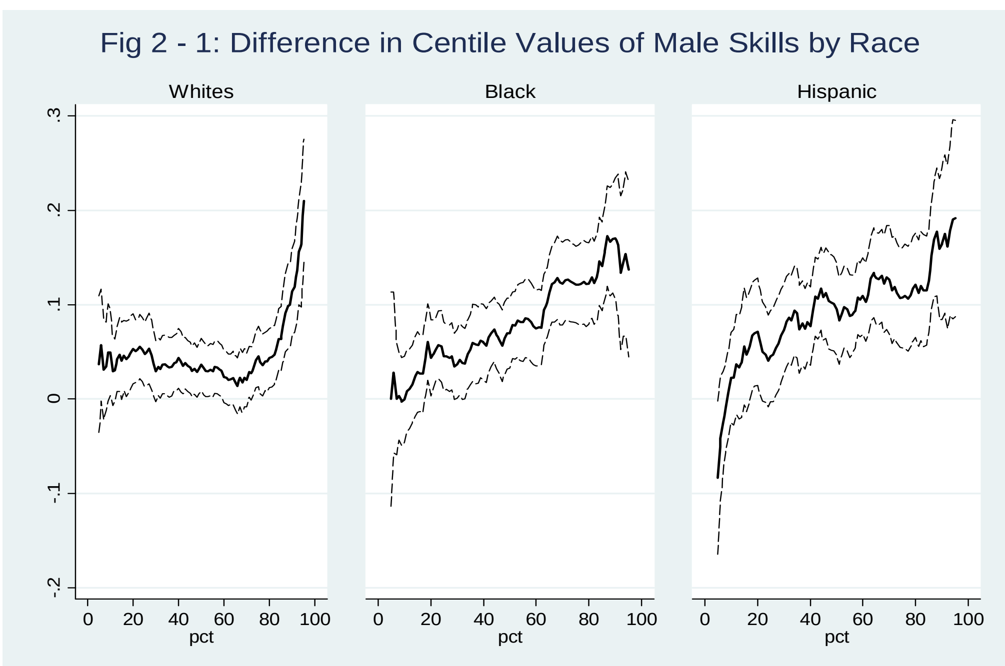
	OLS Regression[2]	Difference in mean characteristics (1997-1979)	Partial Effect of Mean shift on wages	Marginal Effect of Mean Shift on wages	Marginal Effects from DFL (from Table 5)
	(1)	(2)	(3)	(4)	(5)
Overall Change			0.042 (0.005)***	0.042 (0.005)***	0.056 (0.014)***
Race and Sex dummies			0.008 (0.001)***	-0.009 (0.001)***	-0.008 (0.002)***
White Male	0.197 (0.018)***	-0.035			
Black Male	0.030 (0.019)	0.008			
Hispanic Male	0.185 (0.020)***	0.039			
White Female	-0.172 (0.018)***	-0.044			
Black Female	-0.131 (0.018)***	0.003			
Parental Years of Schooling			0.019 (0.004)***	0.066 (0.004)***	0.055 (0.009)***
Mother					
Dummy for missing	0.011 (0.027)	-0.002			
Years of schooling	0.009 (0.003)***	1.196			
Father					
Dummy for missing	0.061 (0.020)**	0.093			
Years of schooling	0.009 (0.002)***	0.291			
Parental presence at age 14			-0.007 (0.003)***	-0.013 (0.002)***	
Mother only	-0.042 (0.013)***	0.164			
Father only	0.010 (0.030)	0.027			
Neither Mother nor Father	-0.033 (0.026)	0.016			
Education					
AFQT	0.005 (0.000)***	2.319	0.012 (0.001)***	-0.002 (0.001)**	0.000 (0.004)
Highest Grade Completed	0.039 (0.004)***	0.471	0.018 (0.002)***	0.010 (0.001)***	0.017 (0.004)***
Work Transition			-0.008 (0.002)***	-0.009 (0.002)***	-0.010 (0.005)**
Work after graduation	0.120 (0.021)***	0.134			
Graduate early	-0.136 (0.021)***	0.105			
Graduate on time	-0.152 (0.022)***	0.005			
Graduate late	-0.205 (0.026)***	0.043			
Constant	6.364 (0.045)***				

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, 24082) = 188.31, N = 24101.

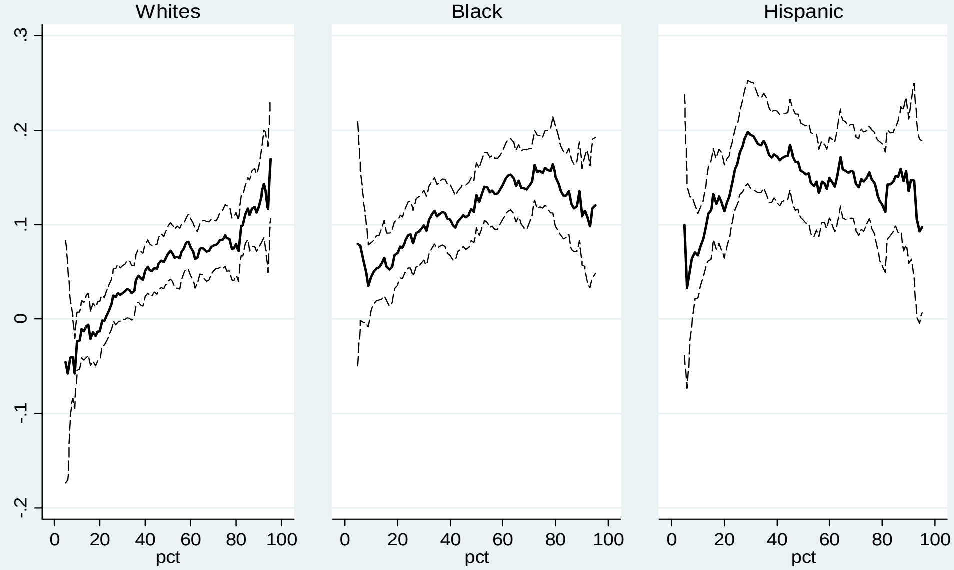


Notes: Depicted are the differences in the centile values for w^{79}-skill index. These differences are obtained by comparing the wage distributions from the reweighted NLSY79 sample with the wage distribution actually observed using the NLSY79 sample. The weights used to reweigh the NLSY79 sample are constructed so as to equalize the distributions of skill correlates in the NLSY79 sample with that observed in the NLSY97 sample. Depicted are four differences in centile values obtained by reweighting to match an increasinly rich set of skill correlates as indicated in the legend.



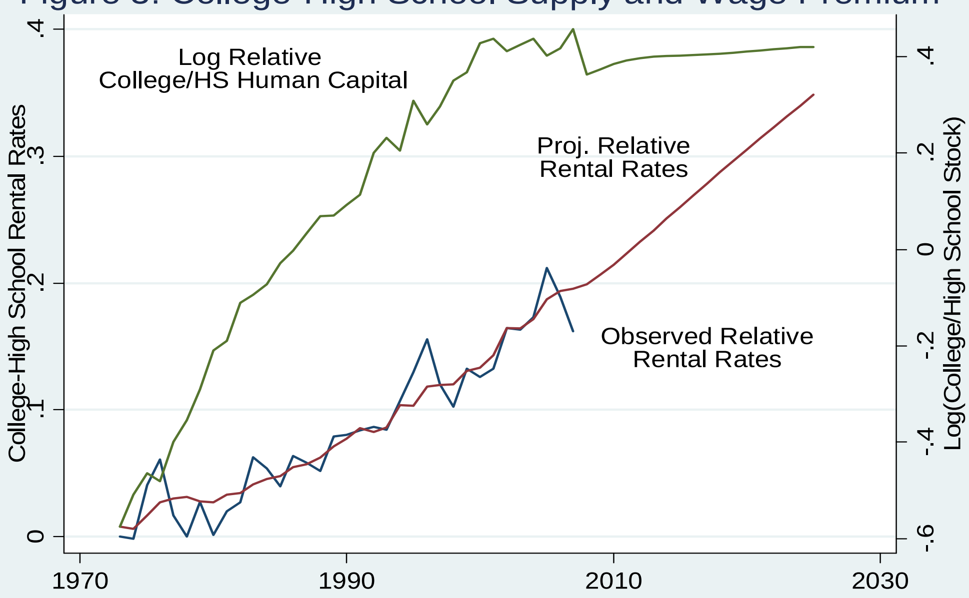
Notes: Depicted are the differences in the centile values for the w^{79}-skill index by race. The set of skill correlates used are race and gender fully interacted with family background variables, AFQT, highest grade completed, and work transition variables. See the notes to Figure 1 for details.

Fig 2 - 2: Difference in Centile Values of Female Skills by Race

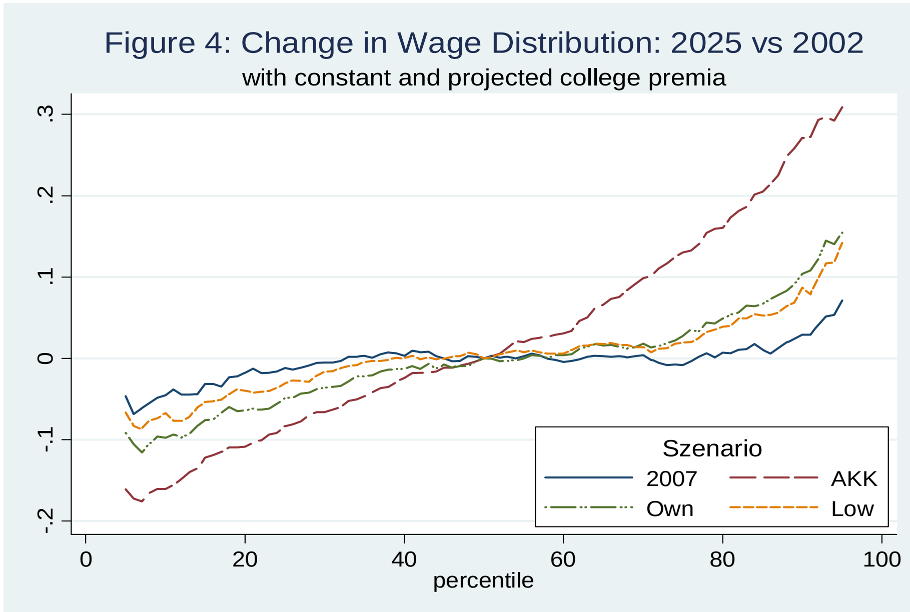


Notes: Depicted are the differences in the centile values for the w^{79}-skill index by race. The set of skill correlates used are race and gender fully interacted with family background variables, AFQT, highest grade completed, and work transition variables. See the notes to Figure 1 for details.

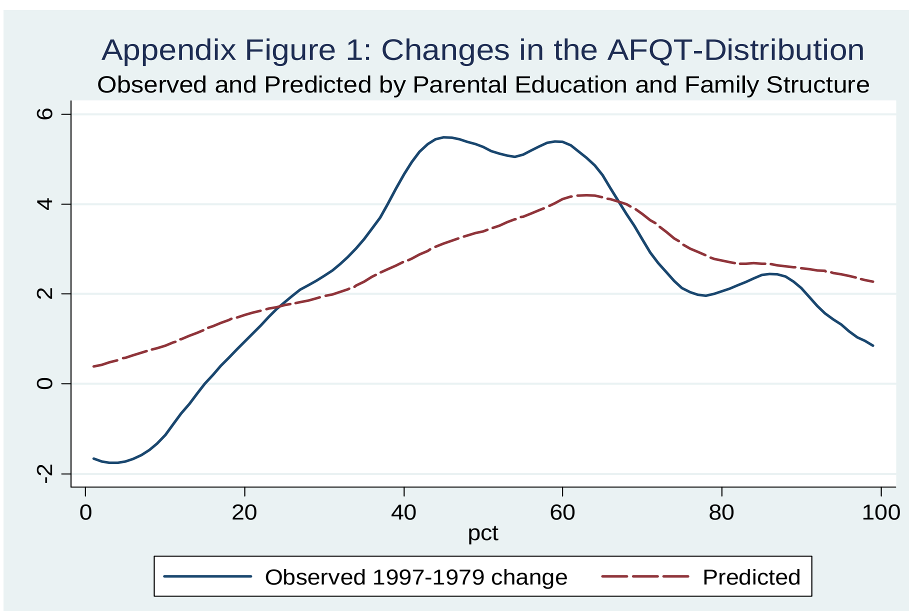
Figure 3: College-High School Supply and Wage Premium



Depicted are the log-ratio of stocks of human capital between 1973 and 2025 as well as the observed and predicted college to high school ratio of human capital rental rates. For details see Section 8.



Depicted are differences in the centile values of the forecasted wages of NLSY97 and observed wages of NLSY79 at age 45. These differences are normalized against the median of the wage distribution. The scenario "2007" refers to 2007 wages with skill distribution of NLSY97. The remaining scenarios combine projections on demand and supply of skill as described in Section 8.
"AKK" has an elasticity of substitution of 2 and SBTC of 2.25%
"Own" has an elasticity of substitution of 6 and a rate of SBTC of 1%
"Low" has an elasticity of substitution of 2 and a rate of SBTC of 1\%



Depicted are actual and predicted differences in the centile values of the AFQT distribution between NLSY97 and NLSY79. The predicted differences are obtained by reweighting the NLSY79 sample to match the NLSY97 by race, gender, parental education, and family structure.

1. Web Appendix: Data Appendix

1.1. **Representativeness of NLSY97.** 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 Enlistment Testing Program 97 sample (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.[1] 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.

1.2. **Sample Selection.** We use survey years 1979-2004 for the NLSY79 and 1997-2006 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.[2] 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

[1] Their comparisons of the Profile of American Youth 80 (PAY80) and Profile of American Youth 97 (PAY97) samples, which are drawn from the same screening surveys as the NLSY79 and NLSY97 (respectively) show that the fraction of 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.

[2] 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.

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.[3]

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.[4] A total of 9,661 (8,901) individuals should have been observed at age 22 in NLSY79 (NLSY97) and are therefore eligible for our analysis.

Web Appendix Table 1 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.[5][6] If we do not condition on observing the AFQT score, we retain about 85% of the base sample.

Our primary method for accounting for AFQT non-response and attrition by age 22 is to construct weights that adjust for attrition based on a large vector of observable characteristics during the base-year interview. We provide more details below. 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).

[3]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.
[4]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.
[5]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.
[6]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.

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

Another problem arises because the scope of the sample is not exactly the same. 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.[7] 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.

1.3. **Attrition and Missing Data on AFQT..** Web Appendix Table 2 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

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

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.[8]

Non-response to the ASVAB is large enough to potentially result in significant biases, especially in the NLSY97. Appendix Table 3 has the same structure as Web Appendix Table 2 and shows how observable characteristics differ depending on whether the AFQT score is missing. The numbers reported in Web Appendix Table 3 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 0.69 years more education by age 22 than those without valid scores but only 0.12 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.[9]

[8]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.

[9]Since the results in Web Appendix Table 3 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.

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.[10] 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.

1.4. **Variable 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: 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: 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.

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

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

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.

Web Appendix Table 4 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. Web Appendix Table 4 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.[11]

Presence of biological parents at age 14[12] 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 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).

[11]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.

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

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.

Web Appendix Table 1: 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**	**8,901**

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

Ought to be present at age 22	**9,661**	**8,901**
	100.00%	***100.00%***
Present at age 22	9,228	7,617
	95.52%	*85.57%*
Excluded if Highest Grade Completed missing	9,201	7,538
	95.24%	*84.69%*
Excluded if AFQT missing	8,822	6,131
	91.32%	*68.88%*

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 1984 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.

Web Appendix Table 2 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)	4,666	71.38%	75.24%	70.68%	4.55 (1.32)***
Black	2,911	14.75%	11.84%	14.89%	-3.05 (1.78)*	2,335	15.60%	13.49%	15.95%	-2.49 (1.06)***
Hispanic	1,851	6.35%	8.35%	6.25%	2.10 (1.22)*	1,901	13.02%	11.27%	13.33%	-2.06 (0.99)**
Sample										
Cross-Sectional Sample	6,082	84.64%	83.74%	84.68%	-0.94 (1.81)	6,667	87.14%	90.08%	86.61%	3.47 (0.98)***
Supplemental Sample	3,579	15.36%	16.26%	15.32%	0.94 (1.81)	2,234	12.86%	9.92%	13.39%	-3.47 (0.98)***
Parental Years of Schooling										
Father										
Years completed (average)	8,215	12.09	12.19	12.09	0.10 (0.18)	6,832	13.16	12.95	13.21	-0.26 (0.10)***
Missing	1446	10.00%	13.24%	9.84%	3.40 (1.50)**	2,069	19.15%	20.58%	11.21%	-9.37 (1.15)***
Mother										
Years completed (average)	9,038	11.78	11.73	11.79	-0.06 (0.13)	8,385	13.05	12.78	13.09	-0.32 (0.08)***
Missing	623	5.12%	7.14%	5.03%	2.11 (1.10)*	516	5.07%	3.88%	5.28%	-1.40 (0.65)**
Parental Presence at age 14										
Mother only	2,378	18.54%	18.69%	18.54%	-0.15 (1.95)	3,496	35.68%	32.39%	36.27%	-3.88 (1.41)**
Father only	278	2.98%	4.09%	2.93%	1.16 (0.85)	501	6.11%	6.94%	5.96%	0.97 (0.70)
Mother and Father	6,545	75.38%	73.33%	75.48%	-2.15 (2.16)	4,386	53.33%	55.22%	52.99%	2.23 (1.47)
Neither Mother nor Father	460	3.09%	3.89%	3.05%	0.84 (0.87)	518	4.88%	5.46%	4.78%	0.68 (0.63)
Total	9,661		4.57%	95.43%		8,901		15.33%	84.67%	

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.

Web Appendix Table 3: 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)	3,911	71.32%	61.78%	73.30%	-11.52 (1.10)***
Black	2,808	14.74%	12.45%	14.84%	-2.38 (1.92)***	2,049	15.63%	19.13%	14.90%	4.23 (1.10)***
Hispanic	1,746	6.31%	9.34%	6.19%	3.15 (1.32)***	1,657	13.06%	19.09%	11.80%	7.29 (1.02)***
Sample										
Cross Sectional Sample	5,819	84.75%	84.18%	84.77%	-0.59 (1.95)	5,642	87.11%	82.09%	88.15%	-6.06 (1.02)***
Supplemental Sample	3,409	15.25%	15.82%	15.23%	0.59 (1.95)	1,975	12.89%	17.91%	11.85%	6.06 (1.02)***
Highest grade completed at age 22										
Years completed (average)	9,201	12.64	11.82	12.68	-0.85 (0.11)***	7,538	13.11	12.53	13.23	-0.69 (0.06)***
Missing	27	0.29%	0.67%	0.27%	0.39 (0.29)	79	0.80%	1.14%	0.74%	0.40 (0.27)
Parental Years of Schooling										
Father										
Years completed (average)	7,858	12.09	11.63	12.11	-0.48 (0.19)**	5,734	13.16	12.52	13.29	-0.76 (0.11)***
Missing	1,370	9.94%	13.01%	9.81%	3.20 (1.62)**	1,883	19.20%	24.36%	18.12%	6.23 (1.19)***
Mother										
Years completed (average)	8,639	11.78	11.36	11.8	-0.44 (0.14)***	7,152	13.05	12.37	13.18	-0.81 (0.09)***
Missing	589	5.09%	8.66%	4.94%	3.72 (1.19)***	465	5.12%	6.21%	4.90%	1.31 (0.67)***
Parental presence at age 14										
Mother only	2,268	18.55%	16.09%	18.66%	-2.56 (2.11)	3,036	35.55%	40.32%	34.56%	5.75 (1.45)***
Father only	263	2.93%	3.99%	2.89%	1.09 (0.91)	416	6.06%	7.08%	5.85%	1.23 (0.72)
Mother and Father	6,260	75.43%	75.33%	75.44%	-0.11 (2.33)	3,732	53.75%	46.69%	55.21%	-8.53 (1.51)***
Neither Mother nor Father	437	3.08%	4.60%	3.01%	1.58 (0.94)*	433	4.65%	5.92%	4.38%	1.54 (0.64)***
Total	**9,228**		**5.92%**	**84.08%**		**7,617**		**19.59%**	**80.41%**	

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.

Web Appendix Table 4: 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	0.94	14, 8706	0.67	0.34	8, 6092	0.95
Specification 2	Cohort X Parental HGC	0.72	14, 7176	0.76	0.73	8, 4519	0.67
Specification 3	Cohort X HGC	0.71	7, 6629	0.65	1.91	4, 6097	0.11

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

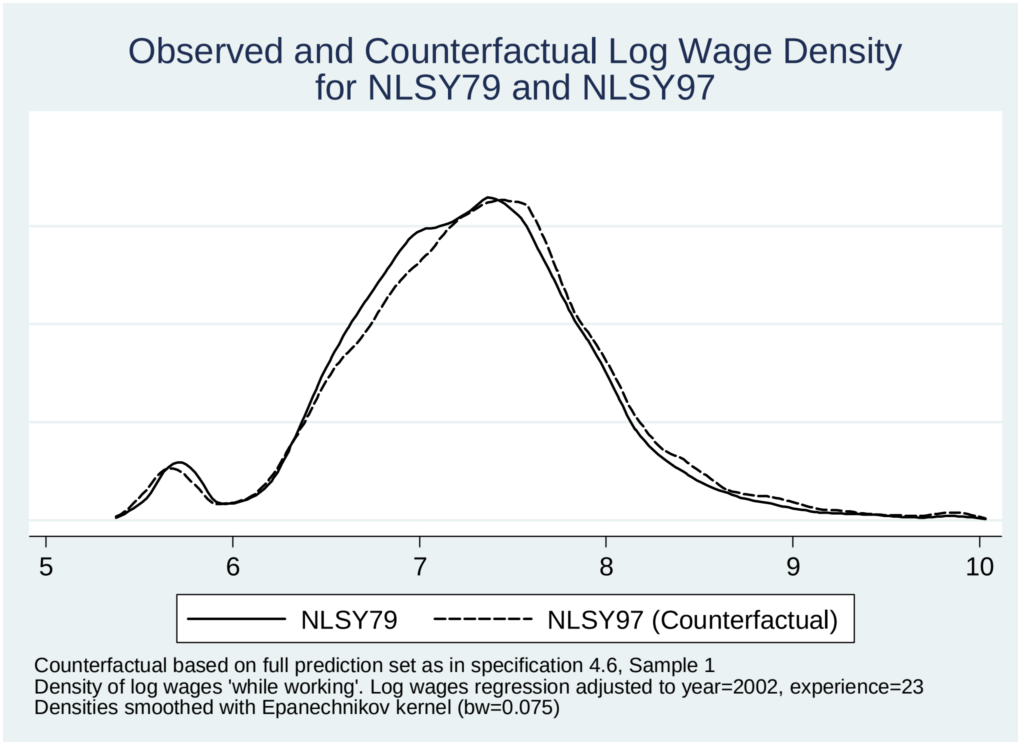
Web Appendix Table 5: The Distribution of Propensity Weights for Different Skill Models				
	Race, Sex	(1) + Family Background	(2) + AFQT, HGC	(3) + Work Transition
	Model 1	Model 4	Model 5	Model 6
	(1)	(2)	(3)	(4)
Smallest	0.75	0.01	0.01	0.001
2nd Smallest	0.75	0.01	0.01	0.001
1%	0.75	0.03	0.02	0.01
5%	0.75	0.11	0.08	0.03
10%	0.75	0.17	0.15	0.05
25%	0.75	0.35	0.30	0.20
50%	0.88	0.67	0.61	0.52
75%	0.93	1.21	1.20	1.20
90%	1.66	1.95	2.06	2.22
95%	1.88	3.01	3.01	3.34
99%	1.89	5.79	6.39	6.74
2nd Largest	1.89	16.43	54.49	66.80
Largest	1.89	17.00	95.18	102.89
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.

Web Appendix Table 6: 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)-(5)	(2) + Highest Grade	(7) + 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	0.053	-0.016	0.010	0.005	0.052	0.012	-0.018
	(0.025)	(0.022)**	(0.012)	(0.010)	(0.019)	(0.033)*	(0.008)	(0.011)
50%	7.489	0.039	-0.016	0.017	-0.006	0.034	0.01	-0.009
	(0.014)	(0.015)**	(0.007)**	(0.006)***	(0.01)	(0.02)*	(0.007)	(0.006)
90%	8.25	0.125	-0.017	0.026	-0.026	0.108	0.025	-0.016
	(0.028)	(0.043)***	(0.017)	(0.017)	(0.015)*	(0.052)**	(0.02)	(0.014)
Mean	7.497	0.057	-0.016	0.017	-0.006	0.052	0.018	-0.017
	(0.014)	(0.018)***	(0.008)**	(0.006)***	(0.009)	(0.023)*	(0.008)**	(0.006)***
Black Male								
10%	6.435	-0.019	0.012	0.000	-0.009	-0.016	0.003	0.009
	(0.023)	(0.027)	(0.009)	(0.010)	(0.028)	(0.041)	(0.011)	(0.009)
50%	7.08	0.063	0.013	0.005	-0.011	0.07	0.003	0.015
	(0.018)	(0.027)**	(0.015)	(0.013)	(0.021)	(0.039)	(0.015)	(0.012)
90%	7.792	0.124	0.029	-0.007	0.021	0.167	-0.008	0.03
	(0.033)	(0.041)***	(0.027)	(0.019)	(0.018)	(0.056)***	(0.021)	(0.025)
Mean	7.104	0.053	0.018	0.001	-0.004	0.068	0.003	0.016
	(0.017)	(0.022)**	(0.013)	(0.011)	(0.014)	(0.031)**	(0.012)	(0.014)
Hispanic Male								
10%	6.525	0.042	0.008	-0.001	-0.025	0.024	0.023	-0.016
	(0.028)	(0.030)	(0.013)	(0.016)	(0.024)	(0.044)	(0.016)	(0.014)
50%	7.286	0.099	0.005	0.005	-0.019	0.09	0.022	-0.012
	(0.028)	(0.029)***	(0.012)	(0.012)	(0.017)	(0.037)**	(0.014)	(0.012)
90%	8.038	0.214	-0.021	0.002	-0.039	0.156	0.006	-0.025
	(0.047)	(0.061)***	(0.033)	(0.03)	(0.026)	(0.08)*	(0.034)	(0.029)
Mean	7.289	0.102	0.001	0.002	-0.023	0.082	0.019	-0.016
	(0.024)	(0.028)***	(0.013)	(0.011)	(0.014)	(0.035)**	(0.012)	(0.012)

Web Appendix Table 6 (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)-(5)	(2) + Highest Grade	(7) + 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%	6.408 (0.016)	0.005 (0.028)	0.000 (0.004)	-0.002 (0.016)	-0.028 (0.02)	-0.025 (0.038)	0.000 (0.015)	-0.002 (0.008)
50%	7.117 (0.016)	0.057 (0.021)**	0.000 (0.007)	0.036 (0.013)***	-0.026 (0.013)**	0.067 (0.029)**	0.044 (0.014)***	-0.008 (0.008)
90%	7.885 (0.022)	0.059 (0.022)**	0.000 (0.006)	0.044 (0.026)*	0.014 (0.012)	0.117 (0.036)***	0.058 (0.027)**	-0.014 (0.011)
Mean	7.128 (0.013)	0.043 (0.015)***	0.000 (0.004)	0.024 (0.009)***	-0.015 (0.008)*	0.052 (0.019)***	0.035 (0.009)***	-0.011 (0.005)***
	Black Females							
10%	6.358 (0.013)	0.009 (0.030)	0.022 (0.014)	0.003 (0.009)	0.010 (0.018)	0.044 (0.039)	0.013 (0.014)	0.012 (0.01)
50%	6.936 (0.017)	0.069 (0.024)**	0.047 (0.025)*	0.008 (0.01)	0.000 (0.018)	0.124 (0.041)***	0.033 (0.017)**	0.022 (0.021)
90%	7.661 (0.022)	0.065 (0.027)**	0.068 (0.029)**	0.000 (0.011)	-0.028 (0.013)**	0.105 (0.043)**	0.035 (0.016)**	0.033 (0.026)
Mean	6.963 (0.014)	0.060 (0.018)***	0.043 (0.016)**	0.005 (0.006)	-0.002 (0.011)	0.106 (0.027)***	0.026 (0.01)***	0.022 (0.014)
	Hispanic Females							
10%	6.392 (0.021)	0.012 (0.03)	0.016 (0.016)	0.025 (0.02)	0.011 (0.025)	0.064 (0.047)	0.044 (0.025)*	-0.003 (0.015)
50%	7.077 (0.027)	0.109 (0.026)***	0.028 (0.015)*	0.021 (0.014)	-0.002 (0.014)	0.156 (0.036)***	0.046 (0.018)***	0.003 (0.01)
90%	7.820 (0.041)	0.135 (0.044)***	0.037 (0.027)	0.000 (0.019)	-0.037 (0.026)	0.135 (0.061)**	0.036 (0.027)	0.001 (0.022)
Mean	7.085 (0.022)	0.087 (0.022)***	0.025 (0.013)*	0.021 (0.012)*	0.001 (0.013)	0.134 (0.031)***	0.047 (0.015)***	-0.001 (0.011)

WEB APPENDIX FIGURE 1



WEB APPENDIX FIGURE 2