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Abstract

In *The Bell Curve*, Herrnstein and Murray (1994) claim, based on evidence from cross-sectional regressions, that differences in wages in the U.S. labor market are predominantly explained by general intelligence. Cawley, Heckman, and Vytlacil (1999), using evidence from random effects panel regressions, reject this claim, in part because returns to general intelligence vary by racial and gender subgroups in their results. In this article, we examine the regression methods used by both sides of the debate and conclude that neither is the appropriate method to analyze the NLSY data that both use. We introduce the Hausman-Taylor estimator to obtain consistent estimated coefficients on the time-invariant general intelligence-related variables and also extend the analysis up through 2002. While many additional socio-economic factors are important explanatory variables in determining the wage rate, the effect of general intelligence on wages is larger in the Hausman-Taylor specification for the 1979-1994 panel than in either the cross-sectional or random effects models, though it becomes statistically insignificant for the 1994-2002 panel. The Hausman-Taylor analysis also indicates no significantly different returns to intelligence by race or gender group.

Keywords: wages; cognitive ability; education

JEL Codes: J24; J31

I Introduction

The Bell Curve: Intelligence and Class Structure in American Life, published in 1994 by Richard Herrnstein (now deceased) and Charles Murray, has been one of the most controversial books of the past several decades. It discusses the variations in intelligence in the United States, illustrates possible causal effects of this intelligence gap on social behavior, and proposes national social policies that acknowledge the existence of an intelligence gap and its impact on American society. Many of the assertions and conclusions are extremely controversial, ranging from the claim that low measured intelligence strongly predicts socially undesirable behavior to the proposition that a genetic factor in cognitive ability is the main reason behind the low IQ test scores of African-Americans (compared to the scores of whites and Asians).

The book received much public attention and became a bestseller soon after it was released. In the first several months of its release, 400,000 copies of the book were sold around the world. Thousands of reviews and commentaries, from both the general public and academia, were written in the wake of the book's publication. Reactions came from economists, sociologists, psychologists, mathematicians, politicians and the press, generating a huge debate over the link between human intelligence and social behaviors. A wide range of topics and issues in social sciences were discussed in the debate, including the psychological concept of intelligence, the validity of IQ and other instruments testing mental ability, the origin of within- and between-group differences in cognitive ability, the relative predictive power of genetic mental aptitudes versus socio-economic status in predicting social success/failure, and the effectiveness of educational training programs, especially those developed to improve intelligence.

This paper focuses on one specific issue: the effect of intelligence on within- and between-group wage rate differences. *The Bell Curve* asserts that cognitive ability is the most important factor in explaining wage differentials. Employing cross-sectional regression analysis, Herrnstein and Murray claim that "the job market rewards blacks and whites of equivalent cognitive ability nearly equally at almost every job category…A Latino, black, and white of similar cognitive ability earn annual wages within a few hundred dollars of one another" (Herrnstein and Murray [1994], p.325, 340). Furthermore, within the same demographic group, native intelligence dominates socio-economic background variables in explaining wage differentials. Overall, *The Bell Curve* argues that the U.S. economy is a meritocracy.

Economists responded vigorously to such claims concerning the wage equation. Fisher et al. (1996) and Cawley et al. (1996, 1999, 2001) both argue that the measure of social and family environment used by Herrnstein and Murray (1984) is inappropriate, and that they have omitted important variables. Hence, *The Bell Curve* may have under-estimated the effect of social and family background on social outcomes. Furthermore, Herrnstein and Murray neglect in their regressions all human capital measures, such as education, due to their belief that ability determines schooling and job-related performance. Employing cross-sectional and panel analysis respectively, Fisher et al. (1996) and Cawley et al. (1996, 1999, 2001) investigate the effect of intelligence on wage differentials using a more complete set of socio-economic background variables and human capital measures. They conclude that cognitive ability is not a dominant factor in explaining wage differentials, with variations in measured cognitive ability explaining only a small proportion of variance in wages across persons, and that the return to ability is not rewarded equally across racial and gender groups.

This article explores the statistical analyses and compares the methodology of both sides of the debate. All of the authors employ the same data set and use similar regression models, yet they arrive at completely different conclusions. First, we replicate the cross-sectional wage regressions in both *The Bell Curve* and Fisher et al. (1996)'s work, noting that the estimated coefficients of the cross-sectional analysis are likely to be biased due to the existence of unobservable individual characteristics. Then, we turn to Cawley et al. (1996, 1999), which utilizes a random effects panel regression model to estimate the *ceteris paribus* effect of measured intelligence on the wage rate.[1] Random effects panel regression eliminates the omitted variable bias resulting from endogenous unobservable characteristics. However, our results indicate that the strict exogeneity assumption is violated for the panel data, so that the estimated coefficients in Cawley et al. are not consistent. Finally, we introduce a random effects panel-estimation technique developed by Hausman and Taylor (1981) as the appropriate regression model to estimate the effect of intelligence on the wage rate.

II Data Set

The data used in this paper come from the National Longitudinal Survey of Youth 1979 (NLSY79), which is administered by the U.S. Department of Labor since 1979 and designed to represent the entire population of American youth. The NLSY79 consists of a randomly chosen sample of 6,111 U.S. civilian youths, a supplemental sample of 5,295 minority and economically disadvantaged civilian youths, and a sample of 1,280 youths on active duty in the military. All youths were between thirteen and twenty-three years of age in 1978. These data include equal numbers of males and females. Roughly 16 percent of respondents are Hispanics[2] and 25 percent are black, indicating an over-sampling of racial/ethnic minorities. Sample weights are provided

[1] We focus on Cawley et al. (1999) rather than their 1996 or 2001 works in terms of specification-matching, though all three papers utilize the same data source and present related findings.
[2] We recognize that "Hispanic" is an ethnicity instead of race and that the concepts of "black" and "Hispanic", or "white" and "Hispanic" are not mutually exclusive. For example, people can be categorized as "white Hispanic" or "black Hispanic". The strict definitions of "white", "black" and "Hispanic" have very subtle and complicated social implications. However, for the purpose of this paper, black, white, and Hispanic are treated as distinct racial/ethnic subgroups.

for each year to estimate how many individuals in the United States each respondent represents.[3] Data are collected yearly from 1979 to 1994 and biennially since 1994;[4] they provide researchers an opportunity to study in detail the experiences of a large group of young adults.[5] The Appendix to this paper contains the coding information for the complete set of variables used in the regressions reported in the paper tables.

The primary focus of the NLSY79 survey is labor force behavior. It includes very detailed questions on a respondent's employment status, yearly earnings, measures of actual labor market experience, tenure with a specific employer, and employer mobility. The survey also includes a wide range of other variables, such as educational attainment, training investments, income and assets, health conditions, marital status, and fertility histories. Moreover, there is an aptitude measure in the NLSY79, namely, the Armed Services Vocational Aptitude Battery Test (the ASVAB Test). In 1980, 11,878 out of the total 12,686 respondents, which is 94 percent of the whole sample, took the ASVAB Test.

Herrnstein and Murray (1994) endorse a one-dimensional, supposedly time-invariant, measure of human intelligence, called general intelligence and denoted *g*. Charles Spearman (1927), a prominent British psychologist, first proposed that a general component can be extracted from a battery of mental tests using *factor analysis*, which is a mathematical transformation of the correlation matrix. This general component, which Spearman dubbed *g*, predicts performance almost as well as the full battery of tests. Spearman's discovery of *g* established the foundation of psychometrics,[6] and introduced the idea that cognitive ability might

[3] The design of sampling weights involves the reciprocal of the probability of selection at the first interview. See *NLSY79 User's Guide*, Section 2.8

[4] Up to the completion of the calculations reported herein, the latest NLSY79 survey year with available data is 2002.

[5] *NLSY79 User's Guide*, Section 2.8, p.3.

[6] Psychometrics is a branch of psychology that deals with the design, administration, and interpretation of quantitative tests for the measurement of psychological variables such as intelligence, aptitude, and personality traits.

be a unitary trait that is highly heritable and normally distributed in the population, just like height and weight.

Herrnstein and Murray (1994) extract this measure of general intelligence from the ASVAB Test in the NLSY79. However, instead of using *g* directly in their regressions, Herrnstein and Murray use the Armed Services Qualification Test (AFQT), which is composed of four subtests of the ASVAB Test,[7] as the measure of cognitive ability. They justify this approximation of *g* by arguing that the AFQT tests are highly *g*-loaded, i.e. tests that have high correlations with the extracted *g*.[8] Thus, the AFQT scores behave sufficiently similar to *g*.

However, the assumption that human intelligence is unidimensional has been questioned by other psychologists;[9] economists have also cautioned that IQ test scores are at best an imperfect proxy for human intelligence. Neal and Johnson (1996) demonstrate that, contrary to the assumption that intelligence is exogenous and immutable, the AFQT test scores can be affected by additional schooling. Heckman (1995) asserts that "AFQT is an achievement test that can be manipulated by educational interventions" (Heckman [1995], p.1103). Fisher et al. (1996) take a further step and assert that the AFQT is really a test that "largely tapped school and school-like learning" (Fisher et al. [1994], p.62).

While the debate over *g* and its legitimacy in approximating innate intelligence is still active today, most economists agree that IQ tests reflect *some* information about individual abilities and are the best available measures of intelligence.[10] Fisher et al. (1996) and Cawley et

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[7] The AFQT score is the sum of four ASVAB subtests, i.e., Word Knowledge, Paragraph Comprehension, Arithmetic Reasoning, and Mathematics Knowledge.
[8] Herrnstein and Murray (1994): 583. Correlations of AFQT subtests with *g*: Word Knowledge (.87), Paragraph Comprehension (.81), Arithmetic Reasoning (.87), and Mathematics Knowledge (.82).
[9] While recognizing the significance of the general intelligence *g*, psychologists also discovered the *group factors* of intelligence that some, but not all, of the tests shared in common (see Thurstone [1947], Carrol [1993]). These group factors have less explanatory power than g but nonetheless are both statistically and numerically significant in predicting test scores. Even Spearman himself reluctantly admitted the existence of *group factors*: "We have now arrived at the '*group factors*' which… are of immense importance, not only theoretically, but also practically" (Spearman [1927], p.222-223).
[10] See the discussions in Cawley et al. (1996), Ashenfelter and Rouse (1999), and Heckman (1995).

al. (1996, 1999) respectively employ the raw AFQT scores and *g* as proxies for measured cognitive abilities in their re-analyses of *The Bell Curve*. In our analysis, we extract *g* from the full battery of the ASVAB tests through a variation of factor analysis called principal component analysis; *g* is formed by taking principal components of the correlation matrix of ASVAB test scores, and then multiplying the component associated with the largest eigenvalue from the test scores matrix. Principal component analysis produces essentially the same results as other factor analysis methods but is affected the least by sampling error.[11]

III Cross-sectional and Panel Analyses

Cross-sectional Regressions

Herrnstein and Murray's analysis on the wage rate is cross-sectional in nature. Instead of utilizing all of the NLSY79 survey years, they focus on the 1989 survey data only. Their measure of the wage rate, the dependent variable, is the log of the hourly wage rate of the current or most recent job reported by the NLSY79 respondents in 1989. The independent variables include the AFQT score, the respondent's socio-economic index as the measure of family background,[12] and age, all normalized. People who are currently enrolled in college are excluded from the sample because their wage rates from mostly on-campus jobs are low regardless of their intelligence.

Regression 1A in table 1 is the closest replication to Herrnstein and Murray's analysis that we could achieve. The log of the hourly pay rate for the respondent's current/most recent job is the dependent variable, while normalized age, parents' SES index, and the AFQT scores are

[11] See Cawley et al. (1996) .

[12] The SES index is formed based on father's education, mother's education, log of family income, and the Duncan Social-Economic Index (SEI) score associated with either father's or mother's occupation (the higher among the two). The SEI score is based on the United States Bureau of the Census, *1950 Census of Population*. Summary statistics on education and income of all the occupations are obtained from the Census and adjusted for age differences among occupations. Then SEI score is constructed for each occupation measured using its age-adjusted median education and income level. For a complete description of the methodology, see Duncan et al. (1972).

the independent variables. All the coefficients are positive and significant at the 1 percent significance level. The coefficient of the normalized AFQT scores is 0.178, compared with the normalized SES index's coefficient of 0.083. Due to the fact that both AFQT and SES are normalized and have the same standard deviation of 1, a higher estimated coefficient indicates a bigger marginal effect on the independent variable. A standard deviation increase in the normalized AFQT score increases the wage rate by 17.8 percent, which is more than twice the effect of a one standard deviation increase of the normalized SES index. This result is consistent with Herrnstein and Murray's conclusion that cognitive ability, measured by AFQT, plays a larger role in determining wage differentials than does family background. Regression 1B then reruns this specification on 2002 NLSY79 respondent data to provide a bridge to other results presented in this paper. Here the coefficients on both AFQT scores and SES index continue to be positive and statistically significant, indeed growing in magnitude, though the AFQT score effect grows by less than the SES index effect as the subject cohort ages; age becomes statistically insignificant as a regressor for the respondent cohort.

Fisher et al. (1996) extend the analysis from the regressions of Herrnstein and Murray (1994). They point out that the measure for social and family background used by Herrnstein and Murray, i.e., the SES index, has "left out many important features of the social environment that affect who is at risk of being poor" (Fisher et al. [1996], p.78). For example, Herrnstein and Murray explain the high correlation between the AFQT test scores and future education levels (r = 0.6 for white males) as a one directional causal effect: that schooling is in itself a signal of cognitive ability. Smarter respondents that score higher on IQ tests will go to colleges and graduate schools, obtain better jobs and enjoy higher living standards; therefore, schooling itself does not directly explain wage differentials. However, Fisher et al. argue that education has an independent and significant effect on the wage rate and should be included in the set of control variables.

In their analysis, Fisher et al. (1996) employ a more complete set of control variables,[13] and conclude that the wage regressions of Herrnstein and Murray suffer from omitted variable bias, resulting in an over-estimation of the effect of the AFQT score on the wage rate. Regression 1C is our replication of Fisher et al. (1996), but using the 2002 respondent data; it confirms their findings. In contrast to equations 1A and 1B, the estimated coefficient for the normalized AFQT scores drops to 0.027 and becomes statistically insignificant. This result shows that a considerable amount of the explanatory power of the AFQT scores on the wage rate can be attributed to the newly included variables. Furthermore, the estimated coefficients on many of the control variables other than the AFQT scores are statistically significant. Notably, the coefficient of years of schooling is 0.069 and significant at the 1 percent level.

We also decompose the SES index into its components in regression 1C. Herrnstein and Murray summed up the normalized father's education, mother's education, family income, and Duncan's Social Economic Index, and averaged the sum to obtain the SES index, thus effectively assigning the same weight to all the four components. However, regression 1C does not provide support for the hypothesis that the four components are equally weighted in their effects on the wage rate. In fact, an F test on the null hypothesis that the coefficients of the four components are equal can be rejected at 5 percent significance level ($F=4.35$, $p>F=0.046$). Thus, breaking the SES index up into its components generates a more accurate measure of the individual impacts of the components. Moreover, we follow Mincer (1974) and define (potential) labor market

[13] The modified list of control variables includes parental home environment (family income, mother's education, father's education, parent's SEI index, and the number of siblings), respondent's adolescent community environment (residence region of the country at age 14), respondent's current family and community background (marital status, number of children, and the local unemployment rate), human capital measures(education, current/most recent job tenure, and labor market experiences), age, race and gender.

experience as age minus schooling minus 6. Thus, age drops out of Regression 1C (as opposed to 1B and 1A) because it is collinear with the combination of education and labor market experience.

Herrnstein and Murray argue that it is *g* that determines future social outcomes, yet curiously they use the AFQT scores as an approximate measure of *g* in their analysis. To correct for any possible error of using AFQT to approximate *g*, we employ normalized *g* in regression 1D. By using AFQT instead of *g*, Herrnstein and Murray may have actually under-estimated the role of general intelligence in explaining wage differentials (the coefficient of the normalized *g* is 0.040, versus 0.027, the coefficient of AFQT in regression 1C; however these are both statistically insignificant; our rerunning of equations 1A and 1B—not herein reported—also show a similar slight upscaling in the weight placed on normalized *g* relative to normalized AFQT). One important observation is that now the coefficient of *g* is no longer greater than those of the social/family factors. For example, an F test between the coefficient of *g* and the coefficient of normalized log of family income shows that we cannot reject the null hypothesis that these two coefficients are equal ($F=0.31$, $p>F=0.575$). Therefore, when the omitted variables are included in the regressions, general intelligence no longer dominates socio-economic background in explanatory power. Moreover, the variable interacting race (Black) with AFQT or *g* is significant at the 1 percent significance level in regressions 1C and 1D, and the interaction of gender (Male) with *g* is significant in 1D; the noninteracted dummies for Hispanic and Male are also statistically significant. Thus, the cross-sectional analysis indicates that the wage rate is not independent of racial/ethnic and gender group affiliation.

The caveat of cross-sectional analysis, however, is that it does not account for unobservable individual characteristics of the respondents. For example, the quality of one's education matters in the determination of one's wage rate. Graduates from better colleges have a better chance to land a higher-paying starting job. As with years of schooling, education quality also changes systematically with intelligence. Better schools tend to be more selective and require a higher score on admission tests, such as the SAT or GRE. Due to the limitation of the NLSY79, these unobservable characteristics cannot be included in the analysis, leading to potentially biased estimators. Thus, we refrain from further interpretations of the cross-sectional regression results.

Panel Regression Results and Interpretation

The random effects panel regression model employed by Cawley et al. (1996, 1999) controls effectively for unobservable factors so that they can obtain consistent estimates. To investigate wage returns to intelligence across different demographic groups, they divide the sample into six sub-samples and run separate regressions for each sub-sample.[14] The intelligence measure, *g*, is derived from principal component analysis. Their control variables include a set of human capital measures: schooling (measured as grades completed), weeks of tenure in the current/most recent job, tenure squared (to account for diminishing return to tenure), labor market experience, and experience squared. Eicker-White standard errors generalized for panel data are used to correct for heteroskedasticity. Their results show that "ability is rewarded unequally in the labor market − workers of a given measured ability receive different wages depending on their race and gender, with these differences being statistically and numerically significant" (Cawley et al. [1999], p. 251).

[14] The six groups are white males, white females, black males, black females, Hispanic males, and Hispanic females.

However, Cawley et al. (1996, 1999) have not verified that the strict exogeneity condition is satisfied in their random effects regression model.[15] Random effects estimates suit the purpose of their analysis better, which examines the estimated coefficient of intelligence on earnings. Cognitive ability, as measured by *g*, is time-invariant in the data set and drops out in the fixed effects model; but the random effects model allows for the possibility of obtaining an estimate for the coefficient of intelligence. However, as indicated by Wooldridge (2005), if the strict exogeneity assumption is violated, the random effects model does not yield consistent estimates and the fixed effects model must be used instead.

Regressions 2A to 2D are designed to test for the strict exogeneity condition. We run separate regressions under both the random and fixed effects specifications. 2A and 2C are the random effects regressions; 2B and 2D are the fixed effects ones.[16] Instead of separating the sample into six sub-samples, we include dummy variables for race and gender, as well as the cross-terms of *g* with the race/gender dummy variables in the panel regressions. Regressions 2A and 2B use annual observations from 1979 to 1994, while 2C and 2D employ biennial data from 1994 to 2002.[17] We have also included several current family and social background variables, namely, marital status for each year, number of children for each year, residence type in each year, and local unemployment rate for each year, in the set of control variables.

Regression 2A, which is a random effects model using annual data from 1979 to 1994, is the closest replication of the econometric analysis of the Cawley et al. (1996) -type specification (though we do not run fully-interacted regressions and these are thus not identical specifications

[15] Two estimation methods are used widely in panel data analysis, namely, the fixed effects model and the random effects model. The fixed effects model allows correlation between the unobservable characteristic and the independent variables. The random effects model requires satisfaction of the strict exogeneity assumption that the unobservable characteristic is not correlated with any independent variable to yield consistent estimates.

[16] We have also run regressions with Eicker-White standard errors for both the fixed and random effects specifications; the results are the same as those in regressions 2A to 2D.

[17] This separation of survey years results from the fact that the NLSY79 data is yearly until 1994 and biennially onwards.

to their analysis). The results are largely consistent with those of Cawley et al. (1996), confirming their conclusion that "the correlations of *g* with wages… are modest compared to those of education… [and] the returns to *g* differ significantly across race and gender: payment is not made for 'ability' alone" (Cawley et al. [1996], p. 17).[18] Furthermore, regression 2C shows a similar pattern to 2A, indicating no significant change in the 1994 to 2002 period from the 1979 to 1994 period. Regressions 2B and 2D are respectively the fixed effects counterparts of 2A and 2C. The Hausman specification test is used to test for the strict exogeneity assumption. For both time periods, we reject the null hypothesis that the strict exogeneity condition is not violated.[19] Hence, for both time periods, the random effects model does not generate consistent estimators. Therefore, Cawley et al. (1996) are not clearly justified in using the random effects model even though it generates evidence supporting their claims.

The intuitive reason for the failure of the random effects model may be that the composite error terms include unobservable individual characteristics, such as education quality, which are correlated with some of the independent variables. As discussed above, education quality may vary systematically with intelligence because colleges use intelligence-tapping tests to differentiate and recruit students. Moreover, education quality should also be correlated with education level. The better is someone's schooling quality, the more likely he/she will be qualified to further his/her education. Thus, the strict exogeneity assumption is violated and the fixed effects model should be used instead of the random effects one.

Due to the fact that *g* is time-invariant in the NLSY79, the fixed effects specification pre-empts a meaningful comparison of the respective marginal effects of *g* and education on the

[18] The coefficient of *g* is 0.042 and the coefficient of education is 0.105; both are significant at the 5 percent significance level. The coefficients of the race/gender dummy variables and their cross-terms with *g* are all statistically significant except for the intercept of the black race dummy.

[19] The Hausman specification test indicates that before 1994, Chi square is 1,174.86, and the probability of p>Chi square is 0.000; after 1994, Chi square is 841.15, and the probability of p>Chi square is 0.000.

wage rate. It also reveals nothing about the possible differences in wage returns to intelligence across demographic groups. However, we can examine the difference in the marginal wage return to education over the two time periods. A closer look at regressions 2B and 2D indicates that the estimated coefficient on education declines from 0.091 in the first period to 0.048 in the second period. The drastic drop can probably be explained by the proposition that the marginal return to education peaks during college years as the marginal pecuniary return of completing a master's degree or a PhD is actually lower than that of completing college (see Jacobsen and Skillman, 2004). Most of the respondents in the NLSY79 had finished college, if they did go to college, before 1994. From 1994 to 2002, changes in education level are due mostly to respondents returning to school for a master's degree or a PhD. Thus, the marginal return of education after 1994 is substantially lower than its value before 1994.

IV The Hausman-Taylor Estimator

Both cross-sectional and panel regressions have advantages and disadvantages. Cross-sectional analysis allows for coefficient estimations on time-invariant variables such as *g*, race, and gender, yet it omits unobservable individual characteristics like the quality of education, potentially causing bias in the estimated coefficients. Panel analysis accounts for unobservable individual characteristics and yields consistent estimates. However, because of the violation of the strict exogeneity assumption in the random effects model, only the fixed effects specification can be used for our purpose, pre-empting any possibility to estimate coefficients on time-invariant variables. Thus, neither the cross-sectional nor the fixed effects model is appropriate for testing these hypotheses.

Hausman and Taylor (1981) offer a solution to this problem. They propose a procedure to estimate a random effects model in which the unobserved individual-level characteristics are correlated with some of the independent variables. Their method applies a Generalized Least Squares transformation with instrumental variables to obtain consistent coefficient estimates.

The model is as follows:

$y_{it} = \tau_t + Z_i\gamma + X_{it}\beta + a_i + u_{it}$

where Z_i is a vector of time-invariant explanatory variables, X_{it} is a vector of time-variant variables, a_i is unobserved individual-level characteristics, and u_{it} is the idiosyncratic error term.

Split $X_{it} = [X_{1it} \;\; X_{2it}]$ $\quad Z_{it} = [Z_{1i} \;\; Z_{2i}]$

where X_{1it} and Z_{1i} are exogenous in the sense that

$\mathrm{E}[X_{1it}\, a_i] = \mathrm{E}[Z_{1i}\, a_i] = 0$ and

$\mathrm{E}[X_{1it}\, u_{it}] = \mathrm{E}[Z_{1i}\, u_{it}] = 0$

X_{2it} and Z_{2i} are endogenous in the sense that

$\mathrm{E}[X_{2it}\, a_i] \neq 0$ and $\mathrm{E}[Z_{2i}\, a_i] \neq 0$ but

$\mathrm{E}[X_{2it}\, u_{it}] = \mathrm{E}[Z_{2i}\, u_{it}] = 0$

The key assumption is that certain variables among the variables X_{1it} and Z_{1i} are uncorrelated with a_i. The variables of X_{1it} "can serve two functions because of their variations across both individuals and time: (i) using deviations from individual means, they produce unbiased estimates of the β's, and (ii) using the individual means, they provide valid instruments for the columns of Z_i that are correlated with a_i" (Hausman and Taylor [1981], p.3). Essentially the Hausman-Taylor model employs instrumental variables from within the regression model itself, which is an advantage of panel data. However, the authors caution that these instrumental variables have to be chosen carefully to ensure that X_{1it} and a_i are not correlated. They also point out that the non-correlation assumption can be verified with the Hausman specification test that compares the Hausman-Taylor model with the fixed effects model.

Another necessary condition for consistent estimation in the Hausman-Taylor model is that the columns of X_{1it} provide sufficient instruments for the columns of Z_{2i}, there must be at least as many exogenous time-varying variables as there are endogenous time-invariant variables. If there are more variables in Z_{2i} than in X_{1it}, the model is under-identified and it does not generate consistent estimates of β and γ.

Hausman and Taylor (1981) apply their model to a wage equation to estimate the returns to schooling, treating cognitive ability as an unobservable individual characteristic. They compare OLS, random effects, fixed effects, and Hausman-Taylor models, recognizing that the potential correlation between individual specific latent ability and schooling, which is time-invariant in their data set, causes the OLS and the random effects model to generate biased coefficients. Then, the authors employ the Hausman specification test to verify that in the Hausman-Taylor model, X_1 and Z_1 are not correlated with a_i. Therefore, they conclude that the Hausman-Taylor model is the most appropriate among these models for estimating the wage equation and returns to schooling because it provides consistent estimated coefficients for time-invariant independent variables.

Various economists have responded favorably to the Hausman and Taylor panel data estimation technique. Baltagi, Bresson and Pirotte (2002) verify that the Hausman-Taylor (HT) estimator is consistent under the non-correlation assumption and should be preferred over the random effects model. Based on the HT estimator, Amemiya and MaCurdy (1986), and Breusch, Mison and Schmidt (1989), have respectively proposed new estimation techniques that, given stronger exogeneity assumptions, generate more efficient estimates than the HT estimator.[20] Overall, the advantages of the Hausman-Taylor model in analyzing panel data are recognized by many economists, who have applied the technique to a wide range of empirical topics, particularly in human capital theory for estimating wage equations.[21]

We use the Hausman-Taylor model in our analysis of the wage equation. Even though the AM and BMS estimators are demonstrated to be potentially more efficient than the HT estimator, both estimators require stronger and more specific assumptions. Without appropriate statistical tests to verify these assumptions, we cannot justify the applications of the AM and BMS estimators to our data set. In contrast, the non-correlation assumption required by the HT estimator can be conveniently tested by the Hausman specification test. Thus, the HT estimator is preferred.

In the context of our panel data set, a_i is the unobserved individual characteristic (education quality), X_{2it} is education level, and Z_{2i} includes all endogenous time-invariant explanatory variables, namely, *g* and all the cross-terms of *g* with race/gender dummy variables. In addition, X_{1it} includes other time-variant variables such as marital status and job tenure and Z_{1i} includes all the race/gender dummy variables. We use the Hausman specification test comparing the Hausman-Taylor model with the fixed effects model to verify the assumption that all the components of X_{1it} and Z_{1i} are independent of education quality.

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[20] The Amemiya and MaCurdy (AM) estimator requires that X_1 and a_i are uncorrelated every point in time. Breusch, Mison and Schmidt (BMS) demonstrate that if one can assume that the time-varying variables in X_2 are correlated with a_i only through a_i's time-invariant components, their estimator is consistent and more efficient than both the HT estimator and the AM estimator. Cornwell and Rupert (1988) and Baltagi and Akom (1990) have conducted empirical studies and confirm that, given correct corresponding exogeneity conditions, the AM and BMS estimators are potentially more asymptotically efficient than the HT estimator.

[21] See Contoyannis and Rice (2000), Heineck (2005), Gardebroek and Lansink (2003), and Peridy (2005).

Regression Results and Interpretation

Regressions 3A to 3E present our results from applying the Hausman-Taylor model to the NLSY79 data set. Regression 3A limits the sample to the survey years 1979 to 1994. The large increase in the coefficient of *g* from 0.042 (2A) to 0.277 (3A) is surprising; note it even exceeds the coefficients found in the cross-sectional analysis reported in Table 1. Note that the two regressions use the same set of data, the same regression equation, and the same independent and dummy variables. Hence, any difference in the estimated coefficients must be the result of the bias caused by the violation of the strict exogeneity assumption in regression 2A. Therefore, by using the random effects model, we have potentially underestimated the marginal effect of *g* on the wage rate. Moreover, in regression 3A, the demographic group interaction terms are not statistically significant. In comparison with regression 2A, in which all of the dummy interaction terms are significant at the 5 percent significance level, regression 3A casts some doubt on the claim by Cawley et al. (1996) that the wage return to intelligence is different across the race and gender demographic groups.

Regression 3A confirms one important claim of *The Bell Curve*'s critics: socio-economic background variables have significant explanatory power in predicting wage differentials. For example, the coefficients on human capital variables such as education, tenure, and labor market experience remain statistically significant in 3A and are close to those in regression 2A in magnitude. Compared with the large difference in the estimated coefficients of *g*, these variables are largely unaffected by the use of the random effects versus the HT estimators. Herrnstein and Murray (1994) ignore the effect of the human capital measures on the wage rate; hence, their estimation of *g*'s explanatory power suffers from omitted variable bias.

Regression 3B is the same specification as 3A except using the 1994 to 2002 data. The change in the coefficient of *g* is negligible.[22] In contrast, the magnitude of the coefficients of the human capital variables, including education, job tenure, and work experience, all decrease significantly. Most changes in education level after 1994 are due to the respondents returning to school for graduate degrees that yield a lower marginal pecuniary return than college degrees. Therefore, the marginal return to education drops in the 1994 to 2002 period. A similar argument can be made concerning job tenure and work experience because both variables have diminishing marginal returns with respect to income. Job tenure and work experience are both positively correlated with the wage rate, but the rate of return actually decreases as tenure and experience accumulate. A graph of wage rate versus job tenure or work experience should be concave, with the slope of the curve, i.e., the marginal wage return, positive but decreasing as tenure/experience increases. After 1994, all the respondents of the NLSY79 are around 40 to 50 years old, and in the later stage of their careers. Thus, they are on the flatter part of the wage-tenure/wage-experience curve, and the marginal return to tenure/experience is expected to be lower than in the 1979 to 1994 time period when they just started working.

The Hausman specification test is employed to compare regressions 3A and 3B to regressions 2B and 2D in the previous section, which are the fixed effects panel regressions on exactly the same set of control variables, in order to verify the legitimacy of the application of the Hausman-Taylor model. The key assumption being tested is that the time-variant control variables, including marital status, number of children, residential region, job tenure, and labor market experience, are not correlated with the unobservable individual characteristics so that they can be used as valid instrumental variables in the model. For both time periods, the null

[22] A Chi square test shows that we cannot reject the null hypothesis that the coefficients of *g* in the two time period are the same: Chi square = 0.00, p>Chi square = 0.986.

hypothesis of non-correlation is not rejected,[23] indicating that the Hausman-Taylor estimators are consistent.

Regressions 3C and 3D add three interaction terms of education with the race/gender dummy variables to the regression of each time period to investigate the possibility of different returns to education across different demographic groups. The coefficient of *g* decreases to 0.243 in both periods (and is statistically insignificant in the later period), probably due to the positive correlation between *g* and individual education level. Similar to 3A and 3B, none of the slope terms of *g* with race/gender dummy variables are statistically significant. Hence, our previous finding of no systematic difference in the marginal wage return to intelligence across the race/gender groups is corroborated. In contrast, the interaction terms of education with both the black and Hispanic race dummy variables in regression 3C are significant at the 5 percent significance level. All things equal, the marginal wage return to education is 0.031 and 0.046 lower for blacks and Hispanics respectively compared to whites. In other words, although one extra year of education increases hourly wage by 10.5 percent for whites, it increases the hourly wage by only 7.4 percent for blacks and 5.9 percent for Hispanics. Furthermore, the cross term of education with the gender dummy is not significant in regression 3C, indicating that males and females earn about the same return to education. The coefficients of other control factors, such as tenure and experience, in regressions 3C and 3D are all identical with those in 3A and 3B.

Comparing regressions 3C and 3D yields some interesting observations. Both the Hispanic-education and black-education cross terms become insignificant after 1994. In addition, the coefficient of the education-gender interaction term is not significant in 3D. Moreover, the coefficients on number of children, marital status, and residence area all become insignificant in 3D. Two possibilities may account for the discrepancies between the two periods. First, a sample

[23] Before 1994: Chi square = 1.01, p>Chi square = 0.999; after 1994: Chi square = 1.10, p>Chi square = 0.999.

selection problem may arise in the 1994 to 2002 time period, which means that some characteristics are similar among the respondents who have voluntarily dropped out of the survey before 1994. For example, if people with lower education levels tend to drop out of the survey more than people with higher education levels, the sample pool of the period 1994 to 2002 will have a higher average education level then the general NLSY79 sample, causing a systematic upward bias in the estimated coefficient on education level. Second, instead of the sample selection problem, the difference in the two periods might result from the structural changes in the sample population. For example, in the first period, most of the respondents grow up from their early twenties, so that they tend to give birth to more children in the first period. With more young children, they spend more time at home, which may affect their wage rates. Some women quit their jobs altogether. In contrast, most respondents seldom have more new-born children in the second period when they are typically above forty years old. Thus, the effect of the number of children on the wage rate may be significant in only the first period.

Regression 3E is designed to test the null hypothesis of no systematic difference between people who remained in the survey and those who dropped out in the first period. We track all remaining respondents in the second period back to the first period and run the same regression from 1979 to 1994 for this group of respondents only. Any systematic difference will yield coefficient estimates in regression 3E that are different from those in regression 3C. The results are very revealing. The estimated coefficients in 3E are extremely similar to those in 3C. The coefficient of *g* records the biggest difference at 0.016, but a Chi square test shows that we still cannot reject the null hypothesis that the two coefficients are the same.[24] Therefore, we cannot reject the null hypothesis of no systematic difference between the samples for the two time periods. We conclude that no significant sample selection problem exists in the second period.

[24] Chi square = 0.03, p>Chi square = 0.8561

Regression 3E shows that differences between the results from the two periods are likely due to structural changes in the sample population over time. Being married, having fewer kids, and living in an urban area are all significantly correlated with higher wage rate in the first period; however, as the respondents grow older, these factors all become less significant in explaining wage differentials in the second period. Although the regression results indicate this structural change, we do not have sufficient information to suggest a testable hypothesis for this temporal structure change from the first period to the second period in the sample. Such information would include how much time one spends on child-caring per child or whether living in the urban area offers a young adult more opportunities to find a well paid job. Moreover, it remains unclear why there is significant differences in the return to education across racial/ethnic subgroups in the first period, but not in the second period.

Overall, the Hausman-Taylor estimators are useful in obtaining consistent coefficient estimates on the time-invariant variable *g* and its cross terms with the racial and gender dummy variables without violating the strict exogeneity assumption. With the Hausman specification test between the fixed effects model and the Hausman-Taylor model, we verify that these estimators are consistent in our analysis. Hence, we provide evidence that Cawley et al. (1996, 1999) may have under-estimated the marginal effect of *g* on wage differentials by employing the random effects specifications. More surprisingly, the wage returns to intelligence appear to be similar across racial and gender groups, while the wage returns to education differ significantly between whites and minorities in the first time period.

V Conclusion

In this paper, we investigate both sides of debate around *The Bell Curve* by replicating the statistical analyses of the wage equation by Herrnstein and Murray and their critics. The cross-sectional regression model used by Herrnstein and Murray (1994) is wrongly specified and the marginal effect of AFQT and *g* on the wage rate is over-estimated relative to that due to other factors. They neglect in their analysis many explanatory factors, such as the human capital measures including education, job tenure, and labor market experience, which contribute significantly to the wage differentials. Moreover, the cross-sectional regression model suffers from omitted variable bias because unobservable individual characteristics, such as quality of education, cannot be included. Cawley et al. (1996, 1999) employ a random effects panel regression to demonstrate that the wage return to intelligence is not uniform across demographic subgroups. However, the strict exogeneity assumption for the random effects model is rejected in our analysis and only the fixed effects model can be applied to the data set. Since intelligence is assumed to be time-invariant and thus drops out of the model, the fixed effects regressions provide little relevant information on the effect of *g* on the wage differentials.

Hausman and Taylor (1981) propose a variation of the random effects model that provides consistent estimators despite the violation of the strict exogeneity condition. Applying the Hausman-Taylor model to the data set, we show that the original random effects model employed by Cawley et al. under-estimates the predictive power of *g* on the wage rate. Our analysis does confirm Fisher et al. (1996) and Cawley et al. (1996, 1999)'s claim that socio-economic background variables and human capital measures are important factors in explaining the wage differentials: education, job tenure, marital status, number of children, residential region, and possibly many more other variables are statistically significant, and cannot be neglected in the analysis of wage equations.

Moreover, although we find no significant evidence for different wage returns to intelligence among racial and gender subgroups, the returns to education do differ across race/ethnicity in the time period from 1979 to 1994. Our analysis indicates structural changes in the wage equation from the first time period to the second one in the coefficients of marriage, number of children, current residents, and race-intelligence cross-terms become insignificant in the second period.[25]

Finally, we acknowledge other issues due to the limitations of the data set. Some important causal variables that might affect one's wage rate are missing in the regression, such as an individual's education quality, his/her adolescent neighborhood conditions (crime rate, average annual income of the community, etc.), and his/her work attitude (work ethics, effort level, etc.). Designing a legitimate way to approximate these missing variables from the NLSY79 is difficult. Also, the NLSY79 contains only one set of mental aptitude measures, namely, the ASVAB Test administered in 1980. As a result, we cannot test an important and fundamental characteristic of intelligence, i.e., that *g* is time-invariant and cannot be altered easily by environmental factors. Instead, we must maintain this property as an assumption throughout the paper. If other sets of the ASVAB scores were available in the later survey years, we could test for any systematic changes in the test scores over time and investigate whether IQ scores can be changed through education or external environment variables. Thus, further research, possibly using a new and more comprehensive data set, is needed to derive more definitive conclusions.

[25] The sepearation of the NLSY79 data into two time periods at this particular breakpoint is dictated by the fact that the NLSY is conducted yearly until 1994 and biennially afterwards; re run two sets of regressions to maintain evenly spaced time periods within each regression. This division point need not capture the right timing of structural changes in the wage equation.

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Table 1: Independent variable is Log of Hourly Wage Rate (Cross-sectional Analysis)

	1A	1B	1C	1D
Time Period	1989	2002	2002	2002
Number of Observations	7799	6156	3352	3352
AFQT_n	0.178**	0.238**	0.027	
	(0.011)	(0.012)	(0.026)	
General Intelligence				0.040
				(0.035)
Age_n	0.031**	-0.015		
	(0.009)	(0.010)		
SES_n	0.083**	0.145**		
	(0.014)	(0.016)		
Family Income_n			0.063*	0.062**
			(0.017)	(0.017)
Mother's Edu_n			-0.035	-0.039
			(0.019)	(0.019)
Father's Edu_n			0.057**	0.056**
			(0.020)	(0.020)
Parents' SEI_n			0.024	0.024
			(0.016)	(0.015)
Siblings_n			0.011	0.014
			(0.015)	(0.015)
Northeast Region			0.100*	0.107*
			(0.044)	(0.049)
Northcentral Region			0.020	0.024
			(0.040)	(0.044)
South Region			0.041	0.049
			(0.043)	(0.046)
Black			-0.016	0.014
			(0.038)	(0.040)
Black*test			0.126**	0.123**
			(0.035)	(0.040)
Hispanic			0.084*	0.094*
			(0.042)	(0.042)
Hispanic*test			0.051	0.047
			(0.036)	(0.037)
Male			0292**	0.270**
			(0.026)	(0.026)
Male*test			0.055	0.069*
			(0.029)	(0.031)
Two-Parent Family			-0.048	-0.048
			(0.029)	(0.029)
Education (2002)			0.069**	0.065**
			(0.010)	(0.010)
Job Tenure (2002)			0.021**	0.021**
			(0.002)	(0.002)
Labor Market Exp (2002)			-0.010	-0.013*
			(0.006)	(0.006)
Married (2002)			0.152**	0.151**
			(0.031)	(0.031)
Children (2002)			0.002	0.001
			(0.013)	(0.013)
Urban (2002)			0.125**	0.127**
			(0.029)	(0.029)
Local Unemployment (2002)			-0.001	-0.001
			(0.006)	(0.006)
constant	2.047**	2.630**	1.369**	1.554**
	(0.008)	(0.009)	(0.235)	(0.242)
R-Squared	0.213	0.185	0.279	0.282

standard errors in parentheses; *significant at 5 percent level ** significant at 1 percent level

Table 2: Independent variable is Log of Hourly Wage Rate (Panel Analysis)

	2A	2B	2C	2D
Regression Model	Random	Fixed	Random	Fixed
Time Period	1979-1994	1979-1994	1994-2002	1994-2002
Number of Observations	96300	96300	32067	32067
General Intelligence	0.042**		0.050**	
	(0.003)		(0.005)	
Black	-0.012		-0.034*	
	(0.010)		(0.016)	
Black*test	0.014**		0.015**	
	(0.004)		(0.006)	
Hispanic	0.063**		0.056**	
	(0.010)		(0.016)	
Hispanic*test	-0.015**		-0.008	
	(0.004)		(0.006)	
Male	0.224**		0.228**	
	(0.007)		(0.011)	
Male*test	-0.013**		-0.001	
	(0.003)		(0.004)	
Education	0.105**	0.091**	0.100**	0.048**
	(0.002)	(0.003)	(0.003)	(0.009)
Job Tenure	0.060**	0.049**	0.034**	0.022**
	(0.001)	(0.002)	(0.002)	(0.002)
Job Tenure^2	-0.003**	-0.002**	-0.001**	-0.001**
	(1.2E-04)	(1.3E-04)	(1.0E-04)	(1.1E-04)
Labor Market Exp	0.086**	0.095**	0.046**	0.073**
	(0.001)	(0.001)	(0.004)	(0.005)
Labor Market Exp^2	-0.002**	-0.002**	-4.5E-04**	-0.001**
	(6.9E-05)	(7.1E-05)	(1.2E-04)	(1.3E-04)
Married	0.040**	0.029**	0.051**	0.012
	(0.004)	(0.005)	(0.008)	(0.011)
Children	-0.018**	-0.015**	0.003	4.8E-04
	(0.002)	(0.003)	(0.004)	(0.005)
Urban	0.087**	0.059**	0.030**	0.006
	(0.006)	(0.007)	(0.007)	(0.008)
Local Unemployment	-0.010**	-0.005**	-0.007**	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.182**	0.083*	0.239**	0.803**
	(0.023)	(0.042)	(0.058)	(0.114)
R-Squared	0.355	0.284	0.280	0.067

standard errors in parentheses; *significant at 5 percent level ** significant at 1 percent level

Table 3: Independent variable is Log of Hourly Wage Rate (Hausman-Taylor Analysis)

	3A	3B	3C	3D	3E
Regression Model	HT	HT	HT	HT	HT
Time Period	1979-1994	1994-2002	1979-1994	1994-2002	1979-1994
Number of Observations	96300	32067	96300	32067	81544
	Time-Invariant Endogenous				
General Intelligence	0.277**	0.275**	0.243**	0.243	0.265*
	(0.094)	(0.133)	(0.088)	(0.134)	(0.109)
Black*test	-0.247	0.153	-0.181	0.197	-0.163
	(0.291)	(0.236)	(0.271)	(0.236)	(0.233)
Hispanic*test	-0.137	-0.125	-0.057	-0.101	-0.108
	(0.081)	(0.101)	(0.076)	(0.105)	(0.105)
Male*test	-0.073	0.065	-0.068	0.093	-0.051
	(0.059)	(0.108)	(0.055)	(0.108)	(0.068)
	Time-Invariant Exogenous				
Black	0.077	0.921**	0.499	1.398**	0.636**
	(0.337)	(0.200)	(0.332)	(0.336)	(0.241)
Hispanic	0.343**	0.429**	0.921**	0.588*	0.952**
	(0.106)	(0.125)	(0.140)	(0.279)	(0.141)
Male	0.153**	0.106**	0.096	0.470*	0.074
	(0.036)	(0.044)	(0.085)	(0.218)	(0.094)
	Time-Variant Endogenous				
Education	0.091**	0.053**	0.105**	0.077**	0.106**
	(0.003)	(0.007)	(0.005)	(0.013)	(0.005)
Black*edu			-0.031**	-0.034	-0.032**
			(0.008)	(0.019)	(0.008)
Hispanic*edu			-0.046**	-0.013	-0.047**
			(0.008)	(0.020)	(0.008)
Male*edu			0.005	-0.027	0.005
			(0.006)	(0.016)	(0.007)
	Time-Variant Exogenous				
Job Tenure	0.050**	0.023**	0.050**	0.023**	0.050**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Job Tenure^2	-0.002**	-0.001**	-0.002**	-0.001**	-0.002**
	(1.21E-04)	(9.96E-05)	(-1.21E-04)	(-9.99E-05)	(-1.27E-04)
Labor Market Exp	0.095**	0.073**	0.095**	0.073**	0.093**
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)
Labor Market Exp^2	-0.002**	-0.001**	-0.002**	-0.001**	-0.002**
	(6.81E-05)	(1.24E-04)	(-6.82E-05)	(-1.24E-04)	(-7.27E-05)
Married	0.028**	0.005	0.027**	0.005	0.030**
	(0.004)	(0.010)	(0.004)	(0.010)	(0.005)
Children	-0.014**	-0.001	-0.014**	-0.001	-0.013**
	(0.002)	(0.005)	(0.002)	(0.005)	(0.003)
Urban	0.060**	0.005	0.060**	0.005	0.066**
	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
Local Unemployment	-0.005**	-0.003**	-0.005**	-0.003**	-0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.203**	0.406**	-0.351**	0.094	-0.389**
	(0.066)	(0.114)	(0.079)	(0.181)	(0.093)

standard errors in parentheses; *significant at 5 percent level ** significant at 1 percent level

Appendix: Variable Coding in Regression Tables

Dependent Variable:	*Description of Variable*
Log of hourly wage rate	Log of hourly rate of pay of current/most recent job in dollars per hour for each survey year
Independent variables:	
Test Results	
AFQT_n	AFQT score, normalized
General Intelligence	First component of principle analysis of AVSAB subtest (*g*)
Individual Characteristics and Adolescent Social Background	
Age_n	Age, normalized
SES _n	Composite measure based on father's education, mother's education, log of family income and the Duncan SEI score associated with father's occupation; normalized
Family Income_n	Log of 1979 total net family income in 2002 dollars, normalized
Mother's Edu_n	Years of education of respondent's mother, normalized
Father's Edu_n	Years of education of respondent's father, normalized
Parents' SEI_n	Duncan SEI in deciles assigned to highest of parents' occupations, normalized
Siblings_n	Number of siblings in 1979, normalized
Black	Dummy=1 for Black
Black*test	Black*test result (AFQT or *g* depending on specification)
Black*edu	Black*education level
Hispanic	Dummy=1 for Hispanic
Hispanic*test	Hispanic*test result (AFQT or *g* depending on specification)
Hispanic*edu	Hispanic*education level
Male	Dummy=1 for male
Male*test	Male* test result (AFQT or *g* depending on specification)
Male*edu	Male* education level
Two-Parent Family	Dummy=1 for living with both parents until age 18
Northeast Region	Dummy=1 for respondent living in the Northeast Region at age 14
Northcentral Region	Dummy=1 for respondent living in the North Central Region at age 14
South Region	Dummy=1 for respondent living in the South Region at age 14
Human Capital Measures and Contemporary Background	
Education	Years of education completed up to each survey year
Job Tenure (and squared)	Number of weeks in current/most recent job in each survey year
Labor Market Exp (and squared)	Labor market experience (age minus schooling minus 6) in each survey year
Married	Dummy=1 for being married in each survey year
Children	Number of children respondent has in each survey year
Urban	Dummy=1 for residence in urban area in each survey year
Local Unemployment	Unemployment rate for local labor market in each survey year based on assignment of mean values to a categorical NLSY variable that identifies six levels of unemployment in three-percentage-point increments