DISCUSSION PAPER SERIES

IZA DP No. 1920

Work Experience as a Source of Specification Error in Earnings Models: Implications for Gender Wage Decompositions

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January 2006

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

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IZA Discussion Paper No. 1920
January 2006

ABSTRACT

Work Experience as a Source of Specification Error in Earnings Models: Implications for Gender Wage Decompositions*

We address the bias from using potential vs. actual experience in earnings models. Statistical tests reject the classical errors-in-variable framework. The nature of the measurement error is best viewed as a model misspecification problem. We correct for this by modeling actual experience as a stochastic regressor and predicting experience using the NLSY79 and the PSID. Predicted experience measures are applied to the IPUMS. Our results suggest that potential experience biases the effects of schooling and the rates of return to labor market experience. Using such a measure in earnings models underestimates the explained portion of the male-female wage gap.

JEL Classification: C81, J24, J31

Keywords: experience, specification error, decomposition, gender

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* We are grateful for comments received at the 2005 SOLE/EALE Annual Meeting, the 2005 American Economic Association Annual Meeting, the 2004 Western Economic Association International 79th Annual Conference in Vancouver, Canada, and from seminar participants at the University of Aberdeen, the University of Oxford, the University of Miami, and the University of Arizona. We would also like to thank Tim Barmby and Solomon Polachek.

I. Introduction

This paper addresses the bias inherent in the use of potential, as opposed to actual, work experience measures in human capital earnings models. At a minimum, traditional (Mincerian) log wage equations employ one's completed schooling, ability (if available), prior work experience, and its square. The latter two variables capture the concave relationship that exists between labor market experience and its pecuniary rewards. Many data sets do not contain actual work histories, however. The 1979 National Longitudinal Survey of Youth (NLSY79) and the Panel Study of Income Dynamics (PSID) are two exceptions and are thus preferable in many instances. Because of their relatively small size and unrepresentativeness, such data sets are not always desirable [Moulton (1986)]. Thus, one is often forced to proxy for actual work experience with potential work experience—measured as the time elapsed since leaving school. Such a measure assumes continuous work histories and abstracts away from employment status (over-, full-, or part-time) and multiple-job holding.

Most researchers seem content using potential work experience measures for males as it is not unreasonable to assume that they have been in the labor force continuously since leaving school. The use of such a measure for females is viewed less favorably, yet no attractive alternatives are readily apparent. In many instances, researchers confine their attention solely to males in order to avoid lapses in labor force participation that occur more often for females as they experience various life-cycle changes. While the focus on males arises from expediency, there may be no reason to exclude females from the analysis. Many researchers have undertaken great efforts to avoid the exclusion of females from their analysis (e.g., Filer, 1992; Blank, 1988; Garvey and Reimers, 1980; Corcoran, 1979; Polachek, 1975; Mincer and Polachek, 1974). The increased and more prominent role of females in the labor force warrants, if not necessitates their inclusion [Fullerton and Byrne (1976)]. While use of the Mincer proxy for work experience has become standard practice, we argue that the use of such a measure for males may still be problematic. Male workers, like their female counterparts, experience employment lapses. Such lapses take two different forms—namely, an active job search while unemployed or a withdrawal from the labor force. It is unreasonable to assume that one's labor market experience is affected in the same way by these two different forms of employment lapses. Furthermore, one would not expect the "return" to unemployed labor force experience to be the same as that of employed labor force experience.

This paper employs data collected from the NLSY79 and the PSID to address measurement error in work experience and to examine the implications for gender wage decompositions. The errors-in-variables framework that is usually assumed to be classical is violated here because the measurement error does not have a mean of zero and is found to be correlated with actual measures of work experience. As an alternative to viewing the problem as one of measurement error, we believe it is more fruitful to think of the problem as one of specification error. We investigate the extent to which actual experience can be predicted from other variables and extend our predicted work experience measures to a data set in which actual measures of work experience are not available—specifically, the 1990 wave of the Integrated Public Use Microdata Sample (IPUMS). The potential work experience measures tend to overstate the effects of schooling and the rates of return to labor market experience. The only exception to the latter is for the females. Our predicted work experience measures generally lead to a substantial reduction in the bias on the schooling and experience coefficients. The single exception arises from the estimated coefficient on experience squared for the NLSY79 females. Furthermore, more of the male-female wage gap is explained when our predicted work experience measures are used in lieu of potential experience.

The paper proceeds in the following fashion: Section II provides the background and literature review. Section III discusses the conceptual framework that underlies the analysis. Section IV discusses the data used in the analysis. Section V presents and discusses the results. Finally, Section VI concludes.

II. Background and Literature Review

Measurement error is a problem commonly faced in applied work. For practical purposes, measurement error in the endogenous variable is not problematic because it is usually assumed to be uncorrelated with the regressors. The R^2 of the regression is smaller, however, because of the additional noise contained in the random error term. Conversely, measurement error in regressors does pose serious problems because it leads to biased and inconsistent OLS estimates. When faced with such a problem, most researchers assume that the measurement error is classical, in the sense that the true regressors and their measurement error are uncorrelated, the random disturbance term and the measurement errors are asymptotically uncorrelated, the measurement errors are normally distributed, and that the measurement errors are uncorrelated among themselves.

The standard assumptions placed on the measurement error typically rise out of convenience and are not usually supported by empirical evidence (e.g., Black et al., 2000). Duncan and Hill (1985) and Rodgers et al. (1993) use administrative records from a large manufacturing firm to verify workers' responses to questions pertaining to earnings and hours worked while Bound and Krueger (1991) and Bound et al. (1994) examine measurement error in longitudinal earnings data. Bollinger (1998) also examines measurement error in panel data but uses a nonparametric methodology. Lee and Sepanski (1995) offer a computationally and analytically simpler method to the nonparametric methodology in consistently estimating regression models with measurement error in the dependent and/or independent variables when validation data are available. In sum, all of these validation studies confirm measurement error in survey data and their findings contradict many of the assumptions made in and implications drawn from classical measurement error models.[1]

Measurement error in other variables contained in traditional (Mincerian) log earnings regressions, specifically that of schooling, has received considerable attention in the twins-based literature. Work in this area originally stemmed from the desire to eliminate the bias due to omitted variables (e.g., ability). Ashenfelter and Krueger (1994) were also able to address measurement error in schooling through the creative use of self- and twin-reported schooling levels. While the rather large estimated rates of return to schooling seem to be an anomaly of their data set, Ashenfelter and Krueger conclude that omitted variables do not bias the rates of return to schooling upwards, as was commonly thought and subsequently reaffirmed, while measurement error in schooling biases the rates downwards. See Ashenfelter and Rouse (1998) and Rouse (1999) for follow-up work.

Flores-Lagunes and Light (2003) expand Ashenfelter and Rouse's data set of identical twins to include pairs of siblings from the NLSY79. They note that most research has assumed classical measurement error (e.g., Ashenfelter and Krueger, 1994; Ashenfelter and Rouse, 1998; Rouse, 1999) while non-classical measurement error has usually been assumed to be mean-reverting (e.g., Black et al., 2000) or "(optimal) prediction error" (e.g., Hyslop and Imbens, 2001). While Flores-Lagunes and Light consider four different measurement error constructs in investigating the causal effect of schooling on wages (none, classical, mean-reverting, and correlated person-specific), Likelihood Ratio tests support the assumption of classical measurement error. The Flores-Lagunes and Light results offer continued support of Ashenfelter and Krueger's instrumental variables strategy to correct for measurement error.

In his efforts to explain Ashenfelter and Krueger's exceptionally high within rates

[1] Measurement error in sensitive topics (i.e. receipt of welfare, income, alcohol use, drug use, criminal history, and embarrassing medical conditions) is examined by Marquis et al. (1986).

of return to schooling, Neumark (1999) uses instrumental variables to correct for the attenuation bias due to measurement error. He concludes that the OLS rates of return to schooling may be the most accurate if the within twin ability bias is large enough to offset the measurement error bias in schooling. Like Griliches (1979), Behrman and Rosenzweig (1999) criticize the first-difference technique because such a method exacerbates the bias towards zero when measurement error exists. This is because differencing does not eliminate the measurement error in this variable, but it does, however, rid the common schooling component.

Several others researchers have abstracted away from the measurement error in schooling that is characteristic of the twins-based literature and have focused on the other explanatory variable in the traditional (Mincerian) log wage equation—specifically, work experience. The issue has been probed, mainly for females, in hopes of addressing the bias that accrues to the OLS estimates when potential work experience measures are employed instead of reported actual experience. Garvey and Reimers (1980) argue that the use of the traditional age minus schooling minus six measure is biased because people do not always complete one grade per year (either due to acceleration or retention) and that one accrues non-work time during one's life. Using the NLSY66, Garvey and Reimers instead construct predicted measures of work experience. Moulton (1986) uses Garvey and Reimers' functional form to predict work experience for an exceptionally large data set constructed from the March 1978 CPS matched with Social Security records. Filer (1992) predicts work experience using occupation-specific equations for the NLSY66 and extends his findings to the 1980 Census Public Use Microdata Tapes. Overall, these papers find marginal benefits from using predicted, as opposed to potential, work experience measures for females.

III. CONCEPTUAL FRAMEWORK

As is evident from the previous discussion, much of the literature on measurement error in human capital models has focused on measurement error in a linear term (e.g., schooling). Several researchers (e.g., Ashenfelter and Rouse, 1998; Behrman and Rosenzweig, 1999) have noted the complications introduced by measurement error in a quadratic variable but few have tackled the problem. It is our intention to examine this issue more closely in the context of specification error. Note that we abstract away from any measurement errors that may arise with respect to age and schooling in the potential experience variable and away from measurement error in the direct measures of actual work experience. The objective here is to determine how the use of potential experience versus direct measures of actual work experience affect parameter estimates in earnings models and inferences about gender wage inequality from wage decompositions. Actual work experience as directly measured is the standard against which potential and predicted work experience effects are compared.

Our discussion of specification error will be framed in the simplest of models—a traditional (Mincerian) log wage equation,

$$Y_i = \beta_0 + \beta_1 S_i + \beta_2 X_i^* + \beta_3 X_i^{*2} + \sum_{i=1}^{K} \alpha_i H_i + \varepsilon_i,\ i = 1, ..., N, \tag{1}$$

where Y is the natural log of the hourly wage, S is the schooling level, X^* is true/actual work experience, H is a set of K other control variables, ε is a random error term, i indexes the individual, and N represents the sample size.[2,3] More compactly, we can express (1) as,

[2]Bound and Solon (1999) discuss classical measurement error in schooling for a log wage model.

[3]For more rigorous theoretical treatments of errors-in-variables models see Y. Amemiya (1985) and Hausman et al. (1991).

$$Y = W^* \gamma + \varepsilon, \tag{2}$$

where Y and ε are (N x 1) vectors, W^* is the (N x $(K+4)$) observation matrix, and γ is the (($K+4$) x 1) coefficient vector. Taking the probability limit of the OLS estimator,

$$plim(\widehat{\gamma}) = \gamma + \Sigma^{-1}_{W^*W^*}\Sigma_{W^*\varepsilon}, \tag{3}$$

which is consistent only if $plim(N^{-1}W^{*\prime}\varepsilon) = \Sigma_{W^*\varepsilon} = 0$. Thus, the regressors, specifically schooling and experience, must be exogenously determined (i.e. uncorrelated with ε).[4]

Now suppose that true work experience, X^*, is unobserved. Instead one observes X, which can be thought of as potential work experience. Couching this in the traditional errors-in-variables model,

$$X_i = X_i^* + v_i, \tag{4}$$

where v is the measurement error. At this point we will assume non-classical measurement error in the sense that v may be correlated with X^* and that the mean of v may not be, and most probably is not, zero.[5] As is traditionally the case we will, however, assume that there is no correlation between v and ε. Later we conduct tests of the classical measurement error assumptions.

[4]Several researchers have noted the endogenous nature of schooling (e.g., Bound and Solon, 1999; Black et al., 2000).

[5]The mean of v could be positive if potential work experience overstates actual work experience, which is likely the case for many females. If, however, potential work experience understates one's actual work experience, which is more likely for those who work over-time or who hold multiple jobs, $E(v)$ would be negative.

The nature of the measurement error we are considering is better viewed as a model misspecification problem. This can be seen by substituting (4) into (1) yielding,

$$Y_i = \beta_0 + \beta_1 S_i + \beta_2 X_i + \beta_3 X_i^2 + \sum_{i=1}^{K} \alpha_i H_i + \varepsilon_i^*, \tag{5}$$

where ε_i^* is,

$$\varepsilon_i^* = \varepsilon_i - \beta_2 v_i - 2\beta_3 X_i^* v_i - \beta_3 v_i^2. \tag{6}$$

More compactly, (5) can be expressed as,

$$Y = W\gamma + \varepsilon^*, \tag{7}$$

where W is the $(N$ x $(K+4))$ new observation matrix, and ε^* is the new $(N$ x $1)$ error vector. The error vector ε^* may be expressed as,

$$\varepsilon^* = \varepsilon - v\beta_2 - 2\left[X^* \odot v\right]\beta_3 - \left[v \odot v\right]\beta_3, \tag{8}$$

where $X^* \odot v$ and $v \odot v$ are Hadamard products (i.e. element by element multiplication between X^* and v and between v and v, respectively).[6]

The probability limit of the OLS estimates is,

$$\begin{aligned} plim(\widehat{\gamma}) &= \gamma + \Sigma_{WW}^{-1}\Sigma_{W\varepsilon} - \Sigma_{WW}^{-1}\Sigma_{Wv}\beta_2 - 2\Sigma_{WW}^{-1}\Sigma_{W,X^*\odot v}\beta_3 \\ &\quad -\Sigma_{WW}^{-1}\Sigma_{W,v\odot v}\beta_3 \\ &= \gamma - \Sigma_{WW}^{-1}\Sigma_{Wv}\beta_2 - 2\Sigma_{WW}^{-1}\Sigma_{W,X^*\odot v}\beta_3 - \Sigma_{WW}^{-1}\Sigma_{W,v\odot v}\beta_3, \end{aligned} \tag{9}$$

assuming $\Sigma_{WW}^{-1}\Sigma_{W\varepsilon} = 0$. Now, with specification error associated with substitution of X for X^*, the asymptotic bias in $\widehat{\gamma}$ consists of three or four terms.

[6] In the present case, $X \odot v = [d(X)]\, v$ and $v \odot v = [d(v)] \odot v$, where $d(X)$ and $d(v)$ are $(N$ x $N)$ diagonal matrices formed by arraying the elements of vectors X and v along the principal diagonal. See Ding and Engle (2001) and Styan (1973) for more details.

Our approach to correcting for specification error consists of modeling actual experience as a stochastic regressor generated from a semi-log model:

$$\ell n\left(X_i^*\right) = Z_i\gamma_1 + \psi_{1i}, \tag{10}$$

where $\psi_{1i} \sim N(0, \sigma_{\psi_1}^2)$ and Z is a set of regressors that includes the regressors in (1) (i.e. $S,\ H$) and a set of identifying variables (i.e. a respondent's age in 1990, a set of occupational dummy variables, and the number of children for females).[7]

The semi-log specification bounds X_i^* away from zero. Our proposed correction procedure uses a predicted measure of actual work experience constructed in the following fashion:

$$\widehat{X_i^*} = \exp\left(Z_i\hat{\gamma}_1 + 0.5\tilde{\sigma}_{\psi_1}^2\right), \tag{11}$$

where $\widehat{\gamma}_1$ is obtained from OLS estimation of (10) and $\tilde{\sigma}_{\psi_1}^2$ is obtained from the method of moments estimator

$$\tilde{\sigma}_{\psi_1}^2 = 2\left[\ell n\left(\sum_i X_i^*\right) - \ell n\left(\sum_i \exp\left(Z_i\hat{\gamma}_1\right)\right)\right]$$

that ensures that the sample mean of $\widehat{X^*}$ is identical to the sample mean of X^*, including even the sample lacking actual work experience (see Oaxaca and Ransom, 2003).[8,9] Since $\ell n\left(X_i^{*2}\right) = 2\ell n\left(X_i^*\right)$ it can be shown that the square of predicted work

[7] Note that the occupational dummies could have been included in the log wage equation. However, in order for the system of equations to be identified Z needs to include some regressors that are not already included in H.

[8] While this procedure can be interpreted as instrumental variables, its motivation does not depend on endogeneity problems. Our motivation is to apply the correction model to data sets lacking information on actual experience.

[9] Instead of predicting X^* directly, one could regress the measurement error, υ, on the set of control variables, Z. Thus, $\widehat{\upsilon}_i = Z_i\widehat{\theta}$ where $\widehat{\theta}$ is unbiased and consistent under the standard assumptions on u, and $\widehat{\upsilon}$ can be used to construct $\widehat{X^*}$. Specifically, for the case in which measurement

experience is obtained from

$$\widehat{X_i^{*2}} = \exp\left(Z_i(2\hat{\gamma}_1) + 0.5\tilde{\sigma}^2_{\psi_2}\right)$$

where

$$\tilde{\sigma}^2_{\psi_2} = 2\left[\ell n\left(\sum_i X_i^{*2}\right) - \ell n\left(\sum_i \exp\left(Z_i(2\hat{\gamma}_1)\right)\right)\right]$$

which restricts the sample mean of $\widehat{X^{*2}}$ to match that of X^{*2}.[10]

Our method of predicting work experience is more general than other methods used in the literature and is unique in its use of a semi-log model. For example, Garvey and Reimers (1980) use the 1968-1973 survey years of the NLSY66 to predict work experience measures for females. They focus on black females and white females ages 19 to 29. Actual work experience is constructed by summing lifetime hours spent working or training and dividing through by 2000. In this analysis OLS and Tobit are used to predict work experience measures by birth cohort. Garvey and Reimers regress the actual measure of work experience on a set of demographic variables which include a respondent's age, schooling level, race, marital status, number and ages of children, and health status. However, they do not extend their findings to data sets lacking actual work experience measures. Instead they compare the estimates obtained between the predicted and potential work experience measures. Filer (1992) uses a set of linear occupation-specific equations to predict work experience

error is additive, $\widehat{X_i^*} = X_i - \widehat{v_i}$, and, $\widehat{X_i^*} = X_i e^{-\widehat{v_i}}$, for the case in which the measurement error is multiplicative. Additionally, further simplification of the additive case yields,

$$\begin{aligned}\widehat{X^*} &= [I_N - Z(Z'Z)^{-1}Z']X + Z(Z'Z)^{-1}Z'X^* \\ &= X - Z\widehat{C} + Z\widehat{\delta},\end{aligned}$$

where I_N is an (N x N) identity matrix, $\widehat{C} = (Z'Z)^{-1}Z'X$, and $\widehat{\delta} = (Z'Z)^{-1}Z'X^*$. Our method of predicting work experience differs from this method in that it omits two terms, X and $-Z\widehat{C}$.

[10]An alternative would be to impose the restriction $\tilde{\sigma}_{\omega_2} = 4\tilde{\sigma}_{\omega_1}$.

for females. He constructs actual measures of years of work experience by summing the weeks worked and dividing through by 52 thus ignoring employment status and multiple job holding. He estimates these equations using pooled data (i.e. 1966-1984) from the NLSY66 and extends his findings to the 1980 Census Public Use Microdata Tapes.

Our empirical implementation of (5) includes completed schooling, marital status, industry dummies, regional dummies, and SMSA (Standard Metropolitan Statistical Area) dummies as the set of control variables, H.[11]

IV. DATA

The data used in this paper come from the NLSY79, the PSID, and the IPUMS. We focus on 1990 because it is a Census year common to all of our data sets and permits analysis of relatively young cohorts as well as a more broadly defined age grouping. The NLSY79 consists of 12,686 young men and women, living in the U.S., who were between the ages of 14 and 22 when the first wave of the survey was conducted in 1979. The PSID is a longitudinal study that began in 1968. There were 4,800 families included in 1968 and the largest amount and most detailed information is collected for the head of the household. For this reason, amongst others, we restrict our sample to heads of household who are between the ages of 18 and 55 in 1990. The IPUMS is a collection of 25 cross-sectional samples spanning the 1850-

[11] Mincer and Polachek (1974) provide a different approach than that used in our paper but not an entirely different model. They argue that the simple Mincer earnings function, which uses potential work experience, is biased due to omitted variables rather than measurement error. Mincer and Polachek decompose potential work experience into actual (or instrumented) work experience and "home time" (i.e. time spent out of the labor force) and derive a segmented earnings function instead. This omitted variables approach may explain why our measurement error is non-classical and one-sided. We thank Solomon Polachek for these comments and insights. For further discussion of the life-cycle division of labor within a family unit see Polachek (1975).

2000 U.S. Census years. To ensure comparability of our results across the data sets, we divided the IPUMS into two samples: 1) individuals between the ages of 25 and 33 in 1990; and 2) heads of household between the ages of 18 and 55 in 1990. The former construction most closely parallels the NLSY79 and the latter the PSID. In this paper, we abstract away from racial/ethnic issues by restricting our attention to whites.

The dependent variable used in the log wage equations is the hourly wage. We construct this measure by dividing the total income from wages and salary by the annual hours worked. For the NLSY79 and the PSID, the construction of the annual hours worked will be discussed below. For the IPUMS this measure is just the product of the weeks worked last year and the usual hours worked per week. The control variables, H, are defined as follows: The schooling variable corresponds to the highest grade completed as of 1990. $MARRIED$ takes on a value of "1" if the individuals were married in 1990 and "0" otherwise (i.e. single, separated, annulled, divorced, or widowed). The industry dummies refer to the 1970 Census of the Population's Industry Classification System. The left-out reference group is public administration. The regional dummies correspond to the Northeast, North Central, West, and South regions of the U.S.. "West" is the omitted regional dummy. The SMSA dummies are: 1) not living in a SMSA; 2) living in a SMSA that is not a central city; 3) living in a SMSA where the central city is unknown; and 4) living in a SMSA with central city known. The omitted reference group is "not living in a SMSA."[12]

The actual work experience measures correspond to the "years" of full-time equiv-

[12] For the PSID, information on a respondent's SMSA is available only until 1986. Alternatively, we considered using city size indicators and rural/urban status. The IPUMS does not contain comparable measures for the city size indicators, however, and including a respondent's rural/urban status does not change the results significantly. Thus, the regressions corresponding to the heads of household, ages 18-55 do not include such measures.

alent (FTE) work experience accumulated as of the 1990 interview. The analysis considers only those who report at least one year of FTE work experience. In constructing this measure for the NLSY79 we used the "hours worked on all jobs" each week for a given calendar year. We summed these figures for 1977 through 1989 and then divided the total by 2080 (40 *hours per week* $*$ 52 *weeks per year*) to obtain a measure of FTE work experience.[13]

Information contained in the PSID family files on the "head's annual hours working for money" in 1967-1982 and the "head's total annual work hours" for 1983-1989 was used to construct actual work experience measures. Again, we summed the annual hours worked and divided through by 2080. Doing so produced figures that were implausibly low.[14] Consequently, we redefined the actual work experience measures for the PSID in the following manner. First, we referenced the information contained in response to the question asking how many years an individual worked since the age of 18 years (inclusive). While the mean value of this variable is reasonable, this question elicited some unrealistic responses. For instance, there were several cases in which an individual reported having worked 98 years! Since this was obviously impossible, due to the fact that the oldest respondent considered was 55 years, we identified such individuals and assigned them the maximum allowable calendar years of work experience possible since the age of 18. Next, we summed the number of years in which annual hours were reported. If,

$$\begin{aligned} & \#\ of\ years\ in\ which\ annual\ hours\ are\ reported \\ > \ & max.\ allowable\ calendar\ years\ of\ work\ experience\ since\ the\ age\ of\ 18, \end{aligned}$$

[13] Note that most often these "years" of work experience do not coincide with calendar years and actual work experience values would differ somewhat with alternative definitions of FTE.

[14] Part of the difficulty in using the PSID data is that the coding scheme does not allow one to distinguish between valid skips (i.e. missing information) and zero values.

then the work experience measure used was simply the cumulative hours reported divided by 2080. If the above inequality did not hold, then we constructed the work experience measure as,

$$\left(\frac{(cumulative\ hours\ reported)/2080}{\#\ of\ years\ in\ which\ annual\ hours\ are\ reported}\right) *$$
$$(max.\ allowable\ calendar\ years\ of\ work\ experience\ since\ the\ age\ of\ 18)\,,$$

which simply amounts to assigning the average annual work hours to those years in which such information was missing, plus the annual work hours as reported in the PSID. Doing so yielded much more reasonable estimates of an individual's work history as of 1990.[15]

The potential work experience measure is calculated as follows,

$$Potential\ Work\ Experience = Age_{1990} - Schooling_{1990} - 6. \tag{12}$$

Our sample consists of white males and females with at least one year of actual (and potential) work experience accumulated as of 1990. We omit individuals who were missing information on any of the aforementioned variables and exclude military

[15] Both the NLSY79 and the PSID provide alternative measures of work experience. Specifically, the NLSY79 work history files contain hours worked in the past calendar year and the number of weeks worked per year. The PSID individual files also contain measures of the hours worked in a given year. Additionally, the PSID has information on the number of years a respondent has worked (full-time) since the age of 18. The number of weeks worked per year and the number of years worked since the age of 18 are obviously better than proxied work experience (i.e. potential measures) but they contain a fair amount of measurement error and do not allow for differences in employment status or multiple-job holding. Blank (1988) finds that while being simultaneously determined, the hours worked per week decision are independent of the weeks worked per year decision. In spite of this we did, however, re-estimate (5) using these alternative definitions and the results do not differ much.

personnel as well. In addition we also exclude Farmers and Farm Managers for the female heads of household regressions.

V. ESTIMATION AND RESULTS

Table 1 provides the descriptive statistics on the work experience measures across the data sets. The males, on average, have more work experience accumulated as of 1990 than the females. The NLSY79 males report 1.7 more years of FTE work experience than the females and the PSID males report 4.5 more years. For both data sets the potential work experience measures overstate time actually spent working. The differences are slight for the males but quite pronounced for the females. The problems are less severe for the NLSY79 because this data set contains a relatively young set of respondents. Overall, the most dramatic difference between the potential and actual work experience measures is for the PSID females; there is a 5.4 year discrepancy between the potential measure (17.8 FTE years) and the actual work experience measure (12.4 FTE years).

The descriptive statistics on the other control variables used in the log wage regressions can be found in the technical appendix which is available from the authors upon request. With few exceptions the sample characteristics were very nearly the same as between NLSY79 and IPUMS for the 25-33 year old group and between PSID and IPUMS for the 18-55 year old heads of household group. The main discrepancy was in the average hourly wage. The average hourly wage was consistently higher in the IPUMS data sets, ranging from only $0.13 higher than the NLSY79 for the young male group to $2.79 higher than the PSID for the 18-55 male heads of household group. The IPUMS hourly wage variable exhibited considerably higher variation as well. Because other sample characteristics match up quite closely, these discrepancies can be attributed to differences in how hourly wages had to be constructed because of differential data restrictions between IPUMS and the other data sets. A mitigating factor is that we are focusing on estimation and wage decomposition differences that arise from using actual and predicted experience compared with potential experience, *within* a given data set.

Based on the log wage regressions (available upon request from the authors) one can assess the extent of the bias correction for the estimated coefficients on schooling and work experience by referencing the absolute and mean percent differences. The absolute percent difference between the estimated coefficients for the log wage regressions using either the predicted or the potential experience measures versus actual work experience is,

$$\left| \frac{\widehat{\beta_k}^{\textit{predicted} \text{ or } \textit{potential}} - \widehat{\beta_k}^{\textit{actual}}}{\widehat{\beta_k}^{\textit{actual}}} \right|. \tag{13}$$

The mean absolute percent difference for the returns to experience is just the average of (13) computed for the separate coefficients on the linear and quadratic experience terms. Regan et al. (2004) shows that in the Mincerian simple schooling model the coefficient on schooling is not identified because 1) this model is not based on an optimization framework, 2) does not control for ability (amongst other variables), and 3) is not concave in schooling. Consequently, one cannot interpret the coefficient on schooling as an internal rate of return. Nevertheless, for our purposes we will follow past convention and treat the coefficient on schooling as the effect of schooling on wages.

Table 2 reports the effects on schooling and experience coefficients from using predicted vs potential experience instead of actual experience. In the log wage regressions for the NLSY79 white males, we find that the effect of schooling is 1.3 vs 37.8 percent off when predicted work experience is used vs potential work experience in lieu of actual work experience. See columns 1 and 2, respectively. Similarly, the estimated coefficients on the linear and quadratic experience terms are 14.5 vs 61.7 and 53.6

vs 95.7 percent off when predicted vs potential work experience is used in place of actual work experience. Thus, the average of the estimated coefficients for the experience variable is 34.0 vs 78.7 percent off when predicted work experience is used rather than potential experience. By comparing columns 1 and 2, one sees that the discrepancy on the schooling and experience coefficients are much larger when using potential work experience, instead of our predicted measure, in the log wage regression. For the NLSY79 females the pattern is similar with the exception of the estimated coefficients on quadratic experience. Using our predicted measure in lieu of potential experience creates a significantly larger departure from the estimated coefficient on actual experience squared. The peculiarities associated with the rates of return to work experience for the NLSY79 females may largely be stemming from the fact that this young sample has not accrued enough work experience to reach the concave portion of their wage-experience profile; the experience squared term only gains statistical significance when we use our predicted measure of work experience.

One can apply similar interpretations to the remaining figures in Table 2 corresponding to the PSID samples. We find that the log wage regressions using potential work experience overstate the effects of schooling relative to those using predicted work experience. With respect to the estimated rates of return to work, we again find that the log wage regressions using our predicted measures of work experience perform much better (relative to our actual experience measures) than those regressions using potential work experience Overall, we can take these findings as continued evidence for the need to employ better proxies than time elapsed since leaving school for female and male work histories when such information is lacking.

Tables 3-6 report our results on the effects of different measures of work experience on the male-female wage gap. We separate out the contributions to the wage decomposition of gender differences in the means and estimated coefficients associated with schooling, experience, and experience squared. The remaining contributions pertain to the constant term and the indicator variables and are summed and listed as 'other variables'. In reporting the estimates of discrimination (or the unexplained differential), the separate discriminatory components corresponding to the constant term and indicator variables are omitted because the estimated coefficients associated with these variables are not invariant to the choice of omitted reference groups [Oaxaca and Ransom (1999)]. Although the detailed endowment effects corresponding to the groups of indicator variables are invariant with respect to the choice of left out reference groups, they are not reported separately because the differences across the alternative measures of work experience were negligible.

Table 3 reports the decomposition results for the 25-33 age group from the NLSY79 sample. The unadjusted male-female wage differential is 0.224 log points. For the log wage regression using actual work experience, the difference in average endowments account for 0.07 log points of the unadjusted wage differential. The partial contributions of schooling and experience to the endowment effect are -0.032 and 0.067, respectively and are reported in column 1. Similarly, for column 2 which corresponds to the log wage regression using predicted work experience, the endowment effects explain about 0.097 log points of the unadjusted wage differential. The schooling and experience endowment effects when using predicted experience correspond very closely to those estimated with actual experience. When work experience is measured as the time elapsed since leaving school (column 3), the endowment effects are 0.006. Thus the use of potential experience would imply that virtually all of the gender wage gap is unexplained. Columns (4) - (6) tell the same story. Using actual or even predicted experience yields lower estimates of discrimination compared with potential experience. We note that the separate estimated effects of the discrimination components differ significantly between actual and predicted experience (columns 4 and 5) although the overall sums do not differ very much. This has largely to do with the problem of capturing concavity of the wage/experience profile for this relatively young group of workers.

Table 4 reports the decomposition results for the 25-33 age group from the IPUMS sample. Actual work experience is missing from the IPUMS data so the comparison is between using a predicted work experience and using potential experience. The unadjusted gender wage gap of 0.223 log points is virtually identical to that from the NLSY79 sample. The endowment effects account for 0.093 log points of the unadjusted gap when using predicted experience (column 1). On the other hand the use of potential experience would imply that virtually none of the unadjusted gap is the result of endowment differences (column 2). Columns 3 and 4 show that the corresponding estimate of discrimination is much smaller when using predicted experience. As was the case with the NLSY79, the use of potential experience would imply that virtually the entire gender wage gap for the 25-33 year olds is the result of discrimination or at best is unexplained.

Turning next to the broader group of workers aged 18 to 55 who are heads of households, we report the decomposition results for the PSID sample in Table 5. The unadjusted gender wage gap is 0.297 log points. Actual and predicted experience yield virtually identical estimates of the contribution of endowments at 0.226 and 0.224 log points, respectively (columns 1 and 2). On the other hand potential experience yields a much lower estimate of the endowment effect (0.167 log points). Accordingly, actual and predicted experience yield virtually identical estimates of discrimination at around 0.07 log points (columns 4 and 5). The use of potential experience implies an estimate of discrimination or of the unexplained gap that is nearly twice (column 6) that obtained from using actual or predicted experience. Unlike the case for the younger workers in the NLSY79 dataset, the individual components of the discrimination estimates are very nearly the same as between actual and predicted experience (columns 4 and 5).

Finally, Table 6 reports the decomposition results for IPUMS sample of workers aged 18 to 55 who are heads of households. The unadjusted gender wage gap for this sample is 0.33 log points. Again, actual work experience is missing from the IPUMS dataset. The decomposition results follow the same pattern as found in the other samples. Endowment effects are larger and discrimination effects are correspondingly smaller when using predicted rather than potential experience.

Our analysis of work experience measures concludes with formal tests of the classical measurement error assumptions. The first hypothesis we test is,

$$H_0 : E(v) = 0;\; H_1 : E(v) \neq 0. \tag{14}$$

Testing the above hypothesis is akin to asking whether the average potential experience is (statistically significantly) different from the average actual experience. The following test statistic is used,

$$\frac{\overline{v}}{\widehat{\sigma}_v/\sqrt{N}} \sim t \rightarrow N(0,1), \tag{15}$$

where $\overline{v} = \frac{\sum_{i=1}^{N} v_i}{N}$ and $\widehat{\sigma}_v^2 = \frac{\sum_{i=1}^{N} (v_i - \overline{v})}{N-1}$. For both definitions of actual work experience in the NLSY79 and the PSID data sets, one can reject the null hypothesis at the five percent level of significance. Hence, the measurement error is non-classical in the sense that its mean is not zero. Referring back to Table 1, one sees that the potential work experience measures overstate the true accumulated work experience which suggests that the means of the measurement errors, on average, are positive.

For the case in which the measurement error is additive, the second hypothesis we test is,

$$H_0 : E(X_i^* v_i) = 0;\; H_1 : E(X_i^* v_i) \neq 0, \tag{16}$$

which is testing whether or not there is covariance between the actual work experience and the measurement error. Testing the above hypothesis involves a regression of the measurement error on the actual work experience to determine if the estimated coefficient on X_i^* is statistically significant. Specifically, because the estimated coefficient on X_i^* is the ratio of covariance between X_i^* and v and the variance of X_i^*. Because the variance of X_i^* cannot be zero, a significant estimated coefficient is rendered only when $cov(X_i^*, v_i) \neq 0$. Similarly, if one assumes a multiplicative measurement error, one simply tests for covariance between $ln\,(X_i^*)$ and v_i. Conducting the aforementioned regression in all cases yields statistically significant estimates of the coefficients on X_i^* and $ln\,(X_i^*)$. Thus, one can reject the null hypothesis and conclude that covariance does in fact exist between the measurement error and the (log) actual work experience measure.

VI. CONCLUDING REMARKS

This paper employs data from the NLSY79, the PSID, and the IPUMS in investigating the bias inherent in human capital models that utilize potential, as opposed to actual, work experience measures. We address the issue in a broader sense by not confining the analysis to women, where the problems of measurement error are well-known and broadly accepted, but by expanding the discussion to include males who also experience lapses of employment. The NLSY79 and the PSID allow us to measure actual work experience and to construct predicted work experience measures that we apply to the IPUMS—a data set lacking individual work histories.

A series of log wage regressions are run utilizing the various measures of work experience – actual, predicted, and potential (as proxied by time elapsed since leaving schooling). On the basis of these findings, we conclude that specification error in work experience not only biases its coefficient but also that of schooling as well; potential work experience overstates the effects of schooling and the rates of return to labor market experience. The only exception to the latter is for the PSID females. Based on the figures in Table 2, the bias on the estimated coefficient of schooling is larger when potential work experience is used instead of our predicted work experience measure in human capital models. The mean absolute percent differences reveal a substantial reduction in the bias on the estimated coefficients on experience when our predicted measures are used. The only exception to this is for the NLSY79 females.

Discussions of wage differentials are always at the forefront of labor economics research. The discontinuous nature of female work patterns in particular, coupled with unemployment spells that affect both genders, and different labor market experiences (e.g., employment status) provide evidence that demands better proxies than potential work experience when actual work histories are lacking. Tables 3-6 support this claim. The wage decompositions suggest that more of the male-female wage gap is explained by the difference in average qualifications when our predicted measures of work experience are used in lieu of potential measures.

This paper does not find support for the assumptions that are typically imposed in discussions of (classical) measurement error. We conduct a test that confirms a non-zero mean for the measurement error. While the average measurement error is positive, there are cases in which potential work experience actually *understate* actual work histories due to over-time work, multiple-job holding, and our imposition of a FTE status. Lastly, we conduct a test that confirms correlation between the measurement error and the true work experience measure. While we assume no covariance between the measurement error and the random error in the log wage equation, we conclude that the measurement error in potential work experience measures is non-classical and that the problem is more fruitfully viewed as one of misspecification.

Instrumental Variables (IV) is the traditional approach taken to correct classical measurement error. This paper has shown, however, that the measurement error in work experience is non-classical. Matters are further complicated because experience enters log wage equations linearly and quadratically as well. While Kelejian (1971) offers an alternative estimation strategy (i.e. non-linear 2SLS), identifying a set of unique instruments is not a trivial task. Basically, the problem with instrumenting potential experience (and its square) is that this assumes that the correct model specification requires potential experience but that in a given data set potential experience is measured with error. Thus, instrumenting potential experience would not solve the model misspecification problem. IV applied to potential experience produces biased wage decomposition components in *both* coefficient estimates and in the predicted mean work experience.

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TABLE 1
WORK EXPERIENCE MEASURES--DESCRIPTIVE STATISTICS

	WHITE MALES, AGES 25-33				WHITE MALES, HEADS OF HOUSEHOLD, AGES 18-55			
	NLSY79 (N=2789)		IPUMS (N=3540)		PSID (N=2892)		IPUMS (N=9098)	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
ACTUAL EXPERIENCE	9.186	3.168	---	---	16.063	9.099	---	---
(ACTUAL EXPERIENCE)^2	94.423	61.396	---	---	340.780	373.201	---	---
PREDICTED EXPERIENCE	9.186	1.982	9.186	2.174	16.063	9.754	16.063	9.888
(PREDICTED EXPERIENCE)^2	94.423	40.927	94.423	44.811	340.780	442.316	340.780	415.802
POTENTIAL EXPERIENCE	9.715	3.265	10.057	3.504	17.129	8.813	18.612	9.293
(POTENTIAL EXPERIENCE)^2	105.027	64.892	113.423	76.242	371.046	350.948	432.748	379.450

	WHITE FEMALES, AGES 25-33				WHITE FEMALES, HEADS OF HOUSEHOLD, AGES 18-55			
	NLSY79 (N=2386)		IPUMS (N=3062)		PSID (N=516)		IPUMS (N=2579)	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
ACTUAL EXPERIENCE	7.495	2.813	---	---	12.385	8.037	---	---
(ACTUAL EXPERIENCE)^2	64.080	42.469	---	---	217.845	266.113	---	---
PREDICTED EXPERIENCE	7.495	1.648	7.495	1.793	12.385	7.357	12.385	7.421
(PREDICTED EXPERIENCE)^2	64.080	28.288	64.080	31.184	217.845	267.480	217.845	282.849
POTENTIAL EXPERIENCE	9.424	3.120	9.610	3.432	17.760	10.435	17.610	9.898
(POTENTIAL EXPERIENCE)^2	98.539	60.642	104.129	70.671	424.093	425.393	408.048	384.718

note: ACTUAL and PREDICTED EXPERIENCE are constructed from hours worked per week for the NLSY79 and from total annual work hours as reported in the family files for the PSID

Source of data: 1990 survey of the NLSY79, the PSID, and the IPUMS

TABLE 2

ABSOLUTE % DIFFERENCES AND MEAN ABSOLUTE % DIFFERENCES FOR ESTIMATED COEFFICIENTS FOR SCHOOLING, EXPERIENCE, AND EXPERIENCE^2

	NLSY79			
	WHITE MALES, AGES 25-33		WHITE FEMALES, AGES 25-33	
	PREDICTED VS. ACTUAL	POTENTIAL VS. ACTUAL	PREDICTED VS. ACTUAL	POTENTIAL VS. ACTUAL
	(1)	(2)	(3)	(4)
ABSOLUTE % DIFF FOR SCHOOLING	1.3%	37.8%	3.2%	11.0%
ABSOLUTE % DIFF FOR EXPERIENCE	14.5%	61.7%	113.7%	115.7%
ABSOLUTE % DIFF FOR EXPERIENCE^2	53.6%	95.7%	334.5%	161.0%
MEAN ABSOLUTE % DIFF FOR EXPERIENCE VARIABLE	34.0%	78.7%	224.1%	138.3%

	PSID			
	WHITE MALES, HEADS OF HOUSEHOLD, AGES 18-55		WHITE FEMALES, HEADS OF HOUSEHOLD, AGES 18-55	
	PREDICTED VS. ACTUAL	POTENTIAL VS. ACTUAL	PREDICTED VS. ACTUAL	POTENTIAL VS. ACTUAL
	(5)	(6)	(7)	(8)
ABSOLUTE % DIFF FOR SCHOOLING	0.2%	19.0%	0.9%	15.3%
ABSOLUTE % DIFF FOR EXPERIENCE	0.8%	8.3%	7.0%	37.2%
ABSOLUTE % DIFF FOR EXPERIENCE^2	11.8%	27.6%	7.6%	50.2%
MEAN ABSOLUTE % DIFF FOR EXPERIENCE VARIABLE	6.3%	18.0%	7.3%	43.7%

note: ACTUAL and PREDICTED EXPERIENCE are constructed from hours worked per week for the NLSY79 and from total annual work hours as reported in the family files for the PSID

Source of data: 1990 survey of the NLSY79 and the PSID

TABLE 3
WAGE DECOMPOSITION: NLSY79
WHITE MALES AND FEMALES, AGES 25-33
(UNADJUSTED MALE/FEMALE WAGE DIFFERENTIAL=0.224)

	ENDOWMENT EFFECTS			DISCRIMINATION		
	ACTUAL	PREDICTED	POTENTIAL	ACTUAL	PREDICTED	POTENTIAL
	(1)	(2)	(3)	(4)	(5)	(6)
SCHOOLING	-0.032	-0.033	-0.045	-0.048	0.001	0.232
EXPERIENCE	0.174	0.149	0.011	0.345	-0.254	0.456
EXPERIENCE^2	-0.107	-0.050	-0.001	-0.153	0.210	-0.083
OTHER VARIABLES	0.034	0.030	0.040	0.011	0.171	-0.388
TOTAL	0.070	0.097	0.006	0.154	0.127	0.218

note: ACTUAL and PREDICTED EXPERIENCE are constructed from hours worked per week for the NLSY79

Source of data: 1990 survey of the NLSY79

TABLE 4
WAGE DECOMPOSITION: IPUMS
WHITE MALES AND FEMALES, AGES 25-33
(UNADJUSTED MALE/FEMALE WAGE DIFFERENTIAL=0.223)

	ENDOWMENT EFFECTS		DISCRIMINATION	
	PREDICTED	POTENTIAL	PREDICTED	POTENTIAL
	(1)	(2)	(3)	(4)
SCHOOLING	-0.024	-0.033	-0.079	-0.096
EXPERIENCE	0.197	0.009	0.041	0.138
$EXPERIENCE^2$	-0.102	0.006	0.023	-0.014
OTHER VARIABLES	0.022	0.032	0.145	0.182
TOTAL	0.093	0.013	0.130	0.210

note: PREDICTED EXPERIENCE is constructed from hours worked per week for the NLSY79

Source of data: 1990 survey of the IPUMS

TABLE 5
WAGE DECOMPOSITION: PSID
WHITE MALES AND FEMALES, HEADS OF HOUSEHOLD, AGES 18-55
(UNADJUSTED MALE/FEMALE WAGE DIFFERENTIAL=0.297)

	ENDOWMENT EFFECTS			DISCRIMINATION		
	ACTUAL	PREDICTED	POTENTIAL	ACTUAL	PREDICTED	POTENTIAL
	(1)	(2)	(3)	(4)	(5)	(6)
SCHOOLING	0.004	0.004	0.005	-0.005	-0.016	0.031
EXPERIENCE	0.160	0.162	-0.025	0.012	-0.020	0.235
EXPERIENCE^2	-0.100	-0.089	0.031	-0.010	0.024	-0.088
OTHER VARIABLES	0.162	0.147	0.156	0.074	0.085	-0.048
TOTAL	0.226	0.224	0.167	0.072	0.073	0.130

note: ACTUAL and PREDICTED EXPERIENCE are constructed from total annual work hours as reported in the family files for the PSID

Source of data: 1990 survey of the PSID

TABLE 6
WAGE DECOMPOSITIONS: IPUMS
WHITE MALES AND FEMALES, HEADS OF HOUSEHOLD, AGES 18-55
(UNADJUSTED MALE/FEMALE WAGE DIFFERENTIAL=0.330)

	ENDOWMENT EFFECTS		DISCRIMINATION	
	PREDICTED	POTENTIAL	PREDICTED	POTENTIAL
	(1)	(2)	(3)	(4)
SCHOOLING	-0.016	-0.019	-0.186	-0.128
EXPERIENCE	0.170	0.041	0.195	0.261
EXPERIENCE^2	-0.095	-0.015	-0.060	-0.056
OTHER VARIABLES	0.079	0.087	0.243	0.157
TOTAL	0.138	0.095	0.192	0.235

note: PREDICTED EXPERIENCE is constructed from total annual work hours as reported in the family files for the PSID

Source of data: 1990 survey of the IPUMS

Technical Appendix

TECHNICAL APPENDIX A.1
DESCRIPTIVE STATISTICS FOR WHITE MALES

	AGES 25-33				HEADS OF HOUSEHOLD, AGES 18-55			
	NLSY79 (N=2789)		IPUMS (N=3540)		PSID (N=2892)		IPUMS (N=9098)	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
MARRIED	0.576	0.494	0.590	0.492	0.801	0.399	0.791	0.407
SCHOOLING	12.920	2.587	13.005	2.550	12.965	2.870	13.346	2.812
AGE	28.635	2.270	29.062	2.564	36.094	8.386	37.958	9.015
TOTAL ANNUAL INCOME FROM WAGES AND SALARY	24447.700	17490.500	24008.900	17352.200	30792.400	29136.000	33389.100	27629.700
HOURLY WAGE	11.354	11.669	13.239	49.602	13.839	13.080	16.626	39.445
AGRICULTURE, FORESTRY, FISHING	0.038	0.191	0.031	0.173	0.029	0.169	0.026	0.158
MINING	0.014	0.119	0.012	0.107	0.012	0.109	0.015	0.120
CONSTRUCTION	0.134	0.341	0.136	0.343	0.102	0.303	0.116	0.321
MANUFACTURING	0.256	0.437	0.243	0.429	0.268	0.443	0.260	0.439
TRANSPORTATION, COMMUNICATIONS, OTHER PUBLIC UTILITIES	0.086	0.281	0.073	0.260	0.103	0.304	0.086	0.281
WHOLESALE AND RETAIL TRADE	0.183	0.387	0.204	0.403	0.173	0.379	0.170	0.376
FINANCE, INSURANCE, REAL ESTATE	0.044	0.206	0.052	0.221	0.043	0.203	0.053	0.223
BUSINESS, REPAIR SERVICES	0.077	0.266	0.064	0.244	0.061	0.239	0.056	0.229
PERSONAL SERVICES	0.019	0.135	0.013	0.112	0.016	0.126	0.013	0.111
ENTERTAINMENT, RECREATION SERVICES	0.014	0.117	0.018	0.132	0.009	0.094	0.014	0.119
PROFESSIONAL, RELATED SERVICES	0.090	0.286	0.100	0.300	0.107	0.309	0.120	0.325
PUBLIC ADMINISTRATION	0.044	0.205	0.056	0.230	0.076	0.266	0.072	0.258
NORTHEAST	0.149	0.356	0.217	0.412	0.177	0.381	0.205	0.403
NORTH CENTRAL	0.284	0.451	0.246	0.431	0.226	0.419	0.259	0.438
SOUTH	0.338	0.473	0.302	0.459	0.365	0.482	0.326	0.469
WEST	0.228	0.420	0.236	0.424	0.232	0.422	0.211	0.408
NOT IN SMSA	0.244	0.430	0.251	0.434	---	---	---	---
NOT CENTRAL CITY	0.341	0.474	0.319	0.466	---	---	---	---
CENTRAL CITY UNKNOWN	0.304	0.460	0.273	0.446	---	---	---	---
CENTRAL CITY	0.111	0.314	0.157	0.364	---	---	---	---

Source of data: 1990 survey of the NLSY79, the PSID, and the IPUMS

TECHNICAL APPENDIX A.2
DESCRIPTIVE STATISTICS FOR WHITE FEMALES

	AGES 25-33				HEADS OF HOUSEHOLD, AGES 18-55			
	NLSY79 (N=2386)		IPUMS (N=3062)		PSID (N=516)		IPUMS (N=2579)	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
MARRIED	0.609	0.488	0.637	0.481	0.006	0.076	0.195	0.397
SCHOOLING	13.326	2.295	13.345	2.315	12.915	2.883	13.541	2.534
AGE	28.749	2.262	28.955	2.570	36.674	9.611	37.150	9.384
TOTAL ANNUAL INCOME FROM WAGES AND SALARY	16345.300	12365.200	15745.200	12760.800	19713.400	13152.700	20040.200	16000.500
HOURLY WAGE	9.566	14.520	9.700	10.497	9.898	5.930	11.348	14.106
AGRICULTURE, FORESTRY, FISHING	0.010	0.100	0.012	0.108	0.010	0.098	0.007	0.086
MINING	0.003	0.054	0.001	0.036	0.004	0.062	0.004	0.065
CONSTRUCTION	0.017	0.128	0.016	0.127	0.008	0.088	0.015	0.121
MANUFACTURING	0.157	0.364	0.153	0.360	0.178	0.383	0.161	0.367
TRANSPORTATION, COMMUNICATIONS, OTHER PUBLIC UTILITIES	0.047	0.211	0.040	0.196	0.041	0.198	0.039	0.194
WHOLESALE AND RETAIL TRADE	0.212	0.409	0.213	0.409	0.174	0.380	0.205	0.404
FINANCE, INSURANCE, REAL ESTATE	0.091	0.288	0.109	0.312	0.081	0.274	0.080	0.271
BUSINESS, REPAIR SERVICES	0.060	0.238	0.056	0.230	0.033	0.179	0.061	0.239
PERSONAL SERVICES	0.053	0.225	0.045	0.207	0.072	0.258	0.035	0.185
ENTERTAINMENT, RECREATION SERVICES	0.011	0.104	0.018	0.132	0.012	0.107	0.014	0.116
PROFESSIONAL, RELATED SERVICES	0.302	0.459	0.296	0.456	0.326	0.469	0.326	0.469
PUBLIC ADMINISTRATION	0.037	0.189	0.042	0.200	0.062	0.241	0.054	0.225
NORTHEAST	0.141	0.348	0.216	0.411	0.203	0.403	0.220	0.414
NORTH CENTRAL	0.273	0.446	0.249	0.433	0.180	0.385	0.231	0.422
SOUTH	0.368	0.482	0.310	0.463	0.380	0.486	0.314	0.464
WEST	0.218	0.413	0.225	0.417	0.236	0.425	0.234	0.424
NOT IN SMSA	0.235	0.424	0.251	0.434	---	---	---	---
NOT CENTRAL CITY	0.344	0.475	0.332	0.471	---	---	---	---
CENTRAL CITY UNKNOWN	0.329	0.470	0.279	0.448	---	---	---	---
CENTRAL CITY	0.092	0.289	0.138	0.345	---	---	---	---

Source of data: 1990 survey of the NLSY79, the PSID, and the IPUMS

TECHNICAL APPENDIX A.3
LOG WAGE REGRESSION FOR WHITE MALES, AGES 25-33

	NLSY79			IPUMS	
	(1)	(2)	(3)	(4)	(5)
CONSTANT	0.528	0.512	0.335	0.582	0.650
	(5.358)***	(2.357)**	(2.425)**	(3.377)***	(5.805)***
SCHOOLING	7.986E-02	8.089E-02	0.110	7.154E-02	9.836E-02
	(18.799)***	(18.762)***	(18.577)***	(18.089)***	(18.537)***
ACTUAL EXPERIENCE	0.103	---	---	---	----
	(7.929)***				
$(\text{ACTUAL EXPERIENCE})^2$	-3.516E-03	---	---	---	----
	(-5.257)***				
PREDICTED EXPERIENCE	---	8.819E-02	---	0.116	---
		(2.063)**		(3.499)***	
$(\text{PREDICTED EXPERIENCE})^2$	---	-1.632E-03	---	-3.352E-03	---
		(-0.800)		(-2.104)**	
POTENTIAL EXPERIENCE	---	---	3.946E-02	---	1.924E-02
			(2.824)***		(1.775)*
$(\text{POTENTIAL EXPERIENCE})^2$	---	---	-1.528E-04	---	6.181E-04
			(-0.227)		(1.239)
MARRIED	0.116	8.092E-02	0.149	6.826E-02	0.130
	(5.551)***	(3.500)***	(7.137)***	(3.241)***	(6.764)***
AGRICULTURE, FORESTRY, FISHING	-0.321	-0.359	-0.310	-0.518	-0.481
	(-4.578)***	(-5.054)***	(-4.362)***	(-7.856)***	(-7.308)***
MINING	0.144	0.122	0.152	-5.253E-02	-2.764E-02
	(1.510)	(1.260)	(1.570)	(-0.560)	(-0.294)
CONSTRUCTION	6.224E-02	4.877E-02	8.563E-02	-9.932E-02	-6.850E-02
	(1.125)	(0.868)	(1.526)	(-2.151)**	(-1.482)
MANUFACTURING	1.200E-02	-3.186E-03	3.877E-02	-5.468E-02	-2.201E-02
	(0.234)	(-0.061)	(0.744)	(-1.268)	(-0.511)
TRANSPORTATION, COMMUNICATIONS, OTHER PUBLIC UTILITIES	1.454E-02	-1.407E-02	5.421E-02	-7.755E-02	-1.867E-02
	(0.250)	(-0.237)	(0.920)	(-1.495)	(-0.363)
WHOLESALE AND RETAIL TRADE	-0.185	-0.210	-0.148	-0.253	-0.204
	(-3.506)***	(-3.897)***	(-2.764)***	(-5.749)***	(-4.655)***
FINANCE, INSURANCE, REAL ESTATE	0.126	0.119	0.139	-0.111	-9.028E-02
	(1.893)*	(1.764)*	(2.060)**	(-1.980)**	(-1.610)
BUSINESS, REPAIR SERVICES	-9.165E-02	-0.112	-7.622E-02	-0.153	-0.124
	(-1.546)	(-1.860)*	(-1.267)	(-2.884)***	(-2.345)**
PERSONAL SERVICES	-0.251	-0.256	-0.248	-0.198	-0.190
	(-2.892)***	(-2.914)***	(-2.817)***	(-2.203)**	(-2.118)**
ENTERTAINMENT, RECREATION SERVICES	-0.291	-0.298	-0.304	-0.186	-0.189
	(-3.037)***	(-3.067)***	(-3.125)***	(-2.362)**	(-2.399)**
PROFESSIONAL, RELATED SERVICES	-0.134	-0.128	-0.143	-0.218	-0.246
	(-2.308)**	(-2.178)**	(-2.426)**	(-4.455)***	(-4.995)***
NORTHEAST	5.307E-02	5.091E-02	6.371E-02	6.794E-02	7.510E-02
	(1.584)	(1.501)	(1.871)*	(2.484)**	(2.738)***
NORTH CENTRAL	-5.072E-02	-4.938E-02	-5.094E-02	-2.252E-03	-2.961E-03
	(-1.807)*	(-1.739)*	(-1.789)*	(-0.083)	(-0.109)
SOUTH	-0.113	-0.114	-0.102	-5.997E-02	-5.206E-02
	(-4.194)***	(-4.184)***	(-3.727)***	(-2.353)**	(-2.037)**
SMSA, NOT CENTRAL CITY	0.159	0.151	0.173	0.236	0.253
	(5.870)***	(5.493)***	(6.319)***	(9.184)***	(9.898)***
SMSA, CENTRAL CITY UNKNOWN	9.508E-02	9.805E-02	0.102	0.141	0.146
	(3.447)***	(3.510)***	(3.649)***	(5.516)***	(5.677)***
SMSA, CENTRAL CITY	0.106	0.115	8.792E-02	0.129	0.100
	(2.830)***	(3.045)***	(2.321)**	(4.183)***	(3.230)***
R^2	0.243	0.224	0.219	0.200	0.196
adj. R^2	0.237	0.218	0.213	0.195	0.191
nobs.	2789	2789	2789	3540	3540
rate of return to experience at 10 years	3.283E-02	5.555E-02	3.640E-02	4.922E-02	3.160E-02

t-values are in parentheses
***=significant at the 1% level for a two-tailed t-test
**=significant at the 5% level for a two-tailed t-test
*=significant at the 10% level for a two-tailed t-test

note: ACTUAL and PREDICTED EXPERIENCE are constructed from hours worked per week and POTENTIAL EXPERIENCE=age-schooling-6

Source of data: 1990 survey of the NLSY79 and the IPUMS

TECHNICAL APPENDIX A.4
LOG WAGE REGRESSION FOR WHITE MALES, HEADS OF HOUSEHOLD, AGES 18-55

	PSID			IPUMS	
	(1)	(2)	(3)	(4)	(5)
CONSTANT	0.951 (12.970)***	0.928 (12.045)***	0.738 (9.515)***	0.959 (20.473)***	0.726 (14.710)***
SCHOOLING	7.596E-02 (19.964)***	7.581E-02 (19.940)***	9.039E-02 (22.190)***	8.275E-02 (34.467)***	9.709E-02 (38.668)***
ACTUAL EXPERIENCE	4.363E-02 (11.938)***	---		---	----
(ACTUAL EXPERIENCE)^2	-8.165E-04 (-9.218)***	---		---	----
PREDICTED EXPERIENCE	---	4.399E-02 (11.273)***		4.615E-02 (18.676)***	---
(PREDICTED EXPERIENCE)^2	---	-7.201E-04 (-8.451)***		-7.731E-04 (-13.250)***	---
POTENTIAL EXPERIENCE	---	---	3.999E-02 (9.201)***	---	4.121E-02 (15.427)***
(POTENTIAL EXPERIENCE)^2	---	---	-5.908E-04 (-5.362)***	---	-5.905E-04 (-8.971)***
MARRIED	0.179 (6.949)***	0.158 (6.074)***	0.165 (6.422)***	9.281E-02 (6.024)***	0.102 (6.663)***
AGRICULTURE, FORESTRY, FISHING	-0.480 (-6.894)***	-0.469 (-6.746)***	-0.475 (-6.867)***	-0.481 (-10.782)***	-0.483 (-10.869)***
MINING	0.131 (1.337)	0.139 (1.416)	0.150 (1.538)	0.168 (3.028)***	0.194 (3.507)***
CONSTRUCTION	-3.690E-03 (-0.076)	1.467E-02 (0.301)	-8.619E-03 (-0.178)	5.837E-03 (0.200)	-7.787E-03 (-0.269)
MANUFACTURING	5.351E-02 (1.286)	5.932E-02 (1.430)	5.812E-02 (1.408)	4.747E-03 (0.184)	1.362E-02 (0.530)
TRANSPORTATION, COMMUNICATIONS, OTHER PUBLIC UTILITIES	9.839E-02 (2.052)**	9.468E-02 (2.109)**	9.547E-02 (2.006)**	3.513E-02 (1.142)	4.411E-02 (1.439)
WHOLESALE AND RETAIL TRADE	-0.139 (-3.176)***	-0.138 (-3.158)***	-0.135 (-3.105)***	-0.136 (-5.015)***	-0.123 (-4.542)***
FINANCE, INSURANCE, REAL ESTATE	-4.466E-02 (-0.739)	-4.469E-02 (-0.741)	-4.755E-02 (-0.793)	5.680E-02 (1.626)	7.221E-02 (2.071)**
BUSINESS, REPAIR SERVICES	-8.000E-02 (-1.466)	-6.203E-02 (-1.138)	-6.571E-02 (-1.213)	-6.729E-02 (-1.959)*	-6.889E-02 (-2.013)**
PERSONAL SERVICES	-0.264 (-3.036)***	-0.272 (-3.127)***	-0.289 (-3.353)***	-0.186 (-3.151)***	-0.202 (-3.452)***
ENTERTAINMENT, RECREATION SERVICES	5.628E-02 (0.504)	5.038E-02 (0.452)	3.129E-02 (0.282)	-7.174E-02 (-1.287)	-0.104 (-1.865)*
PROFESSIONAL, RELATED SERVICES	-2.556E-02 (-0.535)	-2.114E-02 (-0.444)	-4.454E-02 (-0.939)	-0.117 (-4.008)***	-0.134 (-4.603)***
NORTHEAST	0.116 (3.636)***	0.115 (3.611)***	0.108 (3.397)***	5.076E-02 (2.678)***	5.127E-02 (2.713)***
NORTH CENTRAL	-4.904E-02 (-1.642)	-4.907E-02 (-1.647)*	-5.698E-02 (-1.923)*	-6.409E-02 (-3.572)***	-6.613E-02 (-3.698)***
SOUTH	-0.166 (-6.208)***	-0.168 (-6.318)***	-0.171 (-6.467)***	-0.107 (-6.277)***	-0.110 (-6.462)***
R^2	0.277	0.280	0.288	0.241	0.246
adj. R^2	0.272	0.276	0.283	0.240	0.245
nobs.	2982	2892	2892	9098	9098
rate of return to experience at 10 years	2.730E-02	2.959E-02	2.817E-02	3.069E-02	2.940E-02

t-values are in parentheses
***=significant at the 1% level for a two-tailed t-test
**=significant at the 5% level for a two-tailed t-test
*=significant at the 10% level for a two-tailed t-test

note: ACTUAL and PREDICTED WORK EXPERIENCE are constructed from total annual work hours as reported in the family files and POTENTIAL WORK EXPERIENCE=age-schooli

Source of data: 1990 survey of the PSID and the IPUMS

TECHNICAL APPENDIX A.5
LOG WAGE REGRESSION FOR WHITE FEMALES, AGES 25-33

	NLSY79			IPUMS	
	(1)	(2)	(3)	(4)	(5)
CONSTANT	0.568 (5.040)***	0.365 (1.763)*	0.818 (4.797)***	0.471 (2.951)***	0.554 (4.277)***
SCHOOLING	8.347E-02 (15.095)***	8.079E-02 (14.013)***	9.262E-02 (12.386)***	7.749E-02 (16.610)***	0.106 (17.549)***
ACTUAL EXPERIENCE	5.715E-02 (3.043)***	---	---	---	----
$(\text{ACTUAL EXPERIENCE})^2$	-1.129E-03 (-0.911)	---	---	---	----
PREDICTED EXPERIENCE	---	0.122 (2.436)**	---	0.111 (2.940)***	----
$(\text{PREDICTED EXPERIENCE})^2$	---	-4.904E-03 (-1.692)*	---	-3.709E-03 (-1.729)*	----
POTENTIAL EXPERIENCE	---	---	-8.948E-03 (-0.522)	---	4.875E-03 (0.409)
$(\text{POTENTIAL EXPERIENCE})^2$	---	---	6.887E-04 (0.805)	---	7.494E-04 (1.300)
MARRIED	2.584E-02 (1.077)	2.290E-02 (0.943)	2.479E-02 (1.013)	1.810E-02 (0.873)	1.364E-02 (0.629)
AGRICULTURE, FORESTRY, FISHING	-0.328 (-2.516)**	-0.324 (-2.442)**	-0.375 (-2.828)***	-0.238 (-2.300)**	-0.333 (-3.203)***
MINING	7.594E-02 (0.343)	7.722E-02 (0.343)	4.875E-02 (0.216)	-5.829E-02 (-0.211)	-2.415E-02 (-0.087)
CONSTRUCTION	0.100 (0.929)	0.117 (1.057)	4.726E-02 (0.430)	-8.441E-02 (-0.928)	-0.156 (-1.717)*
MANUFACTURING	-6.563E-03 (-0.098)	-4.571E-03 (-0.067)	-1.360E-02 (-0.198)	-0.114 (-2.086)**	-0.120 (-2.180)**
TRANSPORTATION, COMMUNICATIONS, OTHER PUBLIC UTILITIES	6.555E-02 (0.813)	6.604E-02 (0.807)	5.635E-02 (0.685)	3.067E-02 (0.445)	2.578E-02 (0.372)
WHOLESALE AND RETAIL TRADE	-0.201 (-3.070)***	-0.197 (-2.944)***	-0.232 (-3.482)***	-0.277 (-5.211)***	-0.317 (-5.956)***
FINANCE, INSURANCE, REAL ESTATE	-7.193E-02 (-1.008)	-7.339E-02 (-1.015)	-6.870E-02 (-0.944)	-8.495E-02 (-1.503)	-7.088E-02 (-1.245)
BUSINESS, REPAIR SERVICES	-4.658E-03 (-0.061)	2.383E-03 (0.031)	-4.783E-02 (-0.614)	-8.384E-02 (-1.313)	-0.122 (-1.908)*
PERSONAL SERVICES	-0.444 (-5.640)***	-0.442 (-5.491)***	-0.498 (-6.223)***	-0.359 (-5.333)***	-0.396 (-5.878)***
ENTERTAINMENT, RECREATION SERVICES	-0.303 (-2.404)**	-0.299 (-2.342)**	-0.327 (-2.548)**	-0.222 (-2.521)**	-0.228 (-2.575)**
PROFESSIONAL, RELATED SERVICES	-7.504E-02 (-1.172)	-7.196E-02 (-1.100)	-0.111 (-1.703)*	-9.357E-02 (-1.808)*	-0.145 (-2.810)***
NORTHEAST	-4.577E-03 (-0.114)	-6.682E-03 (-0.164)	1.103E-02 (0.269)	7.276E-03 (0.243)	2.651E-02 (0.883)
NORTH CENTRAL	-8.664E-02 (-2.597)***	-8.551E-02 (-2.527)**	-7.621E-02 (-2.242)**	-7.570E-02 (-2.572)**	-6.147E-02 (-2.076)**
SOUTH	-0.127 (-4.023)***	-0.130 (-4.028)***	-0.108 (-3.371)***	-0.108 (-3.856)***	-7.986E-02 (-2.861)***
SMSA, NOT CENTRAL CITY	0.148 (4.645)***	0.140 (4.272)***	0.168 (5.174)***	0.218 (7.910)***	0.255 (9.344)***
SMSA, CENTRAL CITY UNKNOWN	0.170 (5.310)***	0.163 (4.964)***	0.192 (5.895)***	0.129 (4.660)***	0.168 (6.094)***
SMSA, CENTRAL CITY	0.276 (5.940)***	0.268 (5.678)***	0.291 (6.143)***	0.297 (8.655)***	0.319 (9.221)***
R^2	0.226	0.204	0.196	0.234	0.227
adj. R^2	0.220	0.197	0.189	0.229	0.221
nobs.	2386	2386	2386	3062	3062
rate of return to experience at 10 years	3.458E-02	2.404E-02	4.825E-03	3.654E-02	1.986E-02

t-values are in parentheses
***=significant at the 1% level for a two-tailed t-test
**=significant at the 5% level for a two-tailed t-test
*=significant at the 10% level for a two-tailed t-test

note: ACTUAL and PREDICTED WORK EXPERIENCE are constructed from hours worked per week and POTENTIAL WORK EXPERIENCE=age-schooling-6

Source of data: 1990 survey of the NLSY79 and the IPUMS

TECHNICAL APPENDIX A.6
LOG WAGE REGRESSION FOR WHITE FEMALES, HEADS OF HOUSEHOLD, AGES 18-55

DATA SOURCE:	PSID			IPUMS	
	(1)	(2)	(3)	(4)	(5)
CONSTANT	1.039	0.995	0.977	0.774	0.668
	(6.652)***	(5.927)***	(5.824)***	(8.270)***	(6.834)***
SCHOOLING	7.631E-02	7.701E-02	8.801E-02	9.649E-02	0.107
	(9.684)***	(9.590)***	(9.519)***	(20.423)***	(20.909)***
ACTUAL EXPERIENCE	4.264E-02	---	---	---	----
	(5.068)***				
(ACTUAL EXPERIENCE)^2	-7.710E-04	---	---	---	----
	(-3.063)***				
PREDICTED EXPERIENCE		4.563E-02	---	3.040E-02	----
		(4.472)***		(6.247)***	
(PREDICTED EXPERIENCE)^2		-8.297E-04	---	-4.979E-04	----
		(-2.991)***		(-3.927)***	
POTENTIAL EXPERIENCE		---	2.676E-02	---	2.638E-02
			(3.613)***		(6.229)***
(POTENTIAL EXPERIENCE)^2		---	-3.840E-04	---	-4.542E-04
			(-2.039)**		(-4.118)***
MARRIED	-0.316	-0.310	-0.348	1.230E-02	-3.670E-02
	(-1.187)	(-1.146)	(-1.277)	(0.431)	(-1.305)
AGRICULTURE, FORESTRY, FISHING	-0.441	-0.439	-0.430	-0.403	-0.375
	(-2.226)**	(-1.929)*	(-1.880)*	(-2.888)***	(-2.715)***
MINING	3.737E-03	5.644E-04	-8.823E-02	0.197	0.185
	(-0.011)	(0.002)	(-0.260)	(1.115)	(1.046)
CONSTRUCTION	1.647E-02	1.078E-02	3.757E-03	-7.195E-02	-5.786E-02
	(-0.068)	(0.044)	(-0.015)	(-0.697)	(-0.561)
MANUFACTURING	-0.216	-0.204	-0.255	-7.639E-02	-0.113
	(-2.247)**	(-2.091)**	(2.620)***	(-1.354)	(-2.016)**
TRANSPORTATION, COMMUNICATIONS, OTHER PUBLIC UTILITIES	3.949E-02	7.668E-02	3.232E-02	6.777E-02	5.508E-02
	(0.308)	(0.584)	(0.247)	(0.918)	(0.748)
WHOLESALE AND RETAIL TRADE	-0.492	-0.480	-0.546	-0.290	-0.328
	(-5.089)***	(-4.881)***	(-5.604)***	(-5.254)***	(-6.030)***
FINANCE, INSURANCE, REAL ESTATE	-4.641E-02	-2.794E-02	-5.350E-02	-1.903E-02	-1.271E-02
	(-0.433)	(-0.255)	(-0.490)	(-0.307)	(-0.205)
BUSINESS, REPAIR SERVICES	-7.932E-02	-6.604E-02	-9.933E-02	-9.756E-02	-0.122
	(-0.575)	(-0.472)	(-0.708)	(-1.478)	(-1.865)*
PERSONAL SERVICES	-0.554	-0.527	-0.665	-0.333	-0.416
	(-4.842)***	(-4.493)***	(-5.786)***	(-4.285)***	(-5.432)***
ENTERTAINMENT, RECREATION SERVICES	-0.631	-0.614634	-0.683	-9.919E-02	-0.138
	(-3.079)***	(-2.920)***	(-3.258)***	(-0.927)	(-1.295)
PROFESSIONAL, RELATED SERVICES	-0.207	-0.198	-0.243	-0.148	-0.178
	(-2.334)**	(-2.199)**	(-2.691)***	(-2.840)***	(-3.448)***
NORTHEAST	9.368E-02	9.895E-02	7.792E-02	8.860E-02	7.704E-02
	(1.528)	(1.583)	(1.241)	(2.676)***	(2.328)***
NORTH CENTRAL	1.570E-02	7.298E-03	-1.202E-02	-2.280E-02	-4.023E-02
	(0.247)	(0.113)	(-0.185)	(-0.694)	(-1.229)
SOUTH	-7.454E-02	-7.820E-02	-6.201E-02	-8.509E-02	-7.644E-02
	(-1.394)	(-1.432)	(-1.133)	(-2.799)**	(-2.519)**
R^2	0.420	0.400	0.395	0.242	0.244
adj. R^2	0.399	0.378	0.373	0.237	0.239
nobs.	516	516	516	2579	2579
rate of return to experience at 10 years	2.722E-02	2.903E-02	1.908E-02	2.044E-02	1.729E-02

t-values are in parentheses
***=significant at the 1% level for a two-tailed t-test
**=significant at the 5% level for a two-tailed t-test
*=significant at the 10% level for a two-tailed t-test

note: ACTUAL and PREDICTED WORK EXPERIENCE are constructed from total annual work hours as reported in the family files and POTENTIAL WORK EXPERIENCE=age-schooling-

Source of data: 1990 survey of the PSID and the IPUMS