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Structural equation models have provided the foundation for research in social stratification for nearly a decade (Blau and Duncan, 1967; Duncan, Featherman and Duncan, 1972; Sewell and Hauser, 1975). These models specify socioeconomic statuses as functions of social origins and intervening events and achievements. With the cumulation of data and findings researchers have become increasingly concerned with precision and validity in measurement and parameter estimation. Some types of measurement error have been incorporated into substantive analyses of the achievement process using structural equation models which include unobserved variables (Siegel and Hodge, 1968; Jencks, et al., 1972; Bowles, 1972; Bowles and Nelson, 1974; Mason, et al., 1976, Treiman and Hauser, 1976).

Precision is not the central issue in the treatment of measurement error and data quality in socioeconomic achievement models. Incorrect specification of measurement error (e.g., ignoring it) can result in systematic bias in parameter estimates. The size and importance of such biases remain points of controversy. Jencks, et al., conclude that "random measurement error is of relatively little importance in research of the kind described here" (1972:336). Bowles (1972:S222) asserts that "social class background is considerably more important as a determinant of both educational attainment and economic success than has been indicated in recent analogous statistical treatments by Duncan and others." Bowles argues that retrospective reports of parental statuses are much less reliable than respondents' reports of their own attainments and that the effects of origin variables are consequently underestimated.

Patterns of response error have been built into models of the achievement process by obtaining multiple indicators of background and achievement variables and specifying models in which the covariation among the indicators is generated by unobserved "true scores." Figure 1 presents a path diagram of such a model with two measures of each of four variables. The model specifies that the jth measure of the ith variable, x_{ij}, is generated by the true score of that variable, T_i, plus a response error, e_{ij}, which is independent of T_i. That is, the measurement structure is:

(1) $x_{ij} = \lambda_{ij}T_i + e_{ij}$, $(i = 1,\ldots,4;\ j = 1,2)$

The model also specifies a fully recursive causal structure among the true scores:

(2.1) $T_3 = \beta_{31}T_1 + \beta_{32}T_2 + u_1$

(2.2) $T_4 = \beta_{41}T_1 + \beta_{42}T_2 + \beta_{42}T_3 + u_2$.

The method most often used to estimate the parameters of such models has been: first, to estimate (or borrow) the parameters of the error structure; second, to estimate the covariance matrix of true scores; and then to estimate the structural coefficients relating the true scores.

To complete the model, the pattern of covariation among response errors must be specified. When multiple responses are obtained from the same individuals, three types of covariation among response errors appear particularly plausible. First, response errors in the report of a variable may covary with the respondent's true score on that variable. For example, individuals of high status may tend to understate their status while those of law status overstate their status. The implication for the measurement structure would be a nonunit slope of the population regression relating the observed measure, x_{ij}, to the true score, T_i. This type of correlated error is captured by the slope coefficient, λ_{ij}, while maintaining the lack of correlation between T_i and e_{ij}. A second source of covariation in response error would be a tendency for respondents to overstate the consistency between different variables ascertained on a single occasion. This "within-occasion between-variable correlated error" is represented in Figure 1 by the dotted lines showing correlations among the e_{i1}, and among the e_{i2}, for $i = 1,\ldots,4$. A third source of correlated response error would be contamination of the respondent's second report of a given variable by his recollection of the earlier report of that variable. This "within-variable between-occasion correlated errors e_{i1} and e_{i2}, for $i = 1,\ldots,4$.

Unfortunately, attempts to apply models like that in Figure 1 to the achievement process have been limited by a lack of appropriate data, by inadequate specifications, and by crude estimation procedures. Siegel and Hodge (1968), Jencks, et al. (1972), Bowles and Nelson (1974), and Treiman and Hauser (1976) relied on between-occasion correlations of educational attainment, occupational status, and income computed from Census tabulations. To these data, Bowles (1972; Bowles and Nelson, 1974) added findings from matched Census and retrospective reports which were obtained for part of the Chicago pretest sample of the 1962 Occupational Changes in a Generation (OCG) survey (Blau and Duncan, 1967: 457-462). However, none of these data included covariances of measures of different variables ascertained on different occasions, i.e., no correlations between x_{ij} and

$x_{i'j'}$, where $i \neq i'$ and $j \neq j'$, were obtained. This lack of complete covariance information precluded estimation of within-occasion correlated error, and thus the resulting estimates were dependent upon untestable assumptions. Further, these researchers had to rely on tenuous assumptions about relationships between reporting errors in Censuses and in other social surveys.

Bowles (1972) specified within-variable correlated error in his models, but assumed an arbitrary value for these correlations, e.g., $\rho_{e_{i1}e_{i2}} = .5$, rather than estimating them. The size of the error correlations is important, because ignoring positive within-variable correlated errors decreases estimated true score correlations, while positive within-occasion correlated errors have the opposite effect. Bowles did not have enough information to identify either within-variable or within-occasion correlated error; it seems arbitrary that he specified a high level of correlation among errors between measurement occasions, but no such correlations within a single occasion. That is, Bowles's assumptions guaranteed he would obtain upper-bound estimates of intergenerational true score correlations.

The specification of models with variables in standard deviation units rather than in their natural metric has resulted in additional problems in the research of Bowles, Treiman and Hauser, Jencks, et al., and Siegel and Hodge. Data quality assumptions stated in terms of error variances by Bowles and by Siegel and Hodge have been implemented in terms of standardized parameters. Yet these assumptions are not invariant to standardization. Moreover, the identifying information implied by unit slope coefficients in the measurement equations is lost under standardization. In addition, standardized measurement parameters (reliability coefficients) have been applied to heterogeneous populations (Bowles, 1972; Treiman and Hauser, 1976; Jencks, et al., 1972; Featherman, 1972; Kelley, 1973), but the unstandardized parameters (error variances) are more likely to be invariant (Wiley and Wiley, 1970). Finally, measurement parameters have been applied across studies where measurement techniques as well as populations differ. For example, Siegel and Hodge recognized differences in the quality of Census and CPS (Current Population Survey) measurement procedures, but such differences have not always been considered in the "borrowing" of reliability coefficients.

In summary, while strong statements about the effects of measurement error can be found in the existing literature, these statements have been based on inadequate data and models. The issues have been well-stated: Failure to incorporate response error structures into models of the achievement process may lead to underestimates of the effects of social background on schooling and achievement or to overestimates of the effects of schooling on later achievements. Without estimates based upon more comprehensive data and a less restricted specification of error structures, we can accept neither the position of Jencks, et al. (1972) and Siegel and Hodge (1968) that the biases are negligible, nor the position of Bowles (1972) that they are substantial.

1973 OCG Data

Data from the remeasurement program of the 1971 Occupational Changes in a Generation-II study allow us to estimate and test less restrictive models of response error and to assess the effects of plausible error structures on parameters of the achievement process. The 1973 OCG study (Featherman and Hauser, 1975) was designed to achieve a strict replication of the 1962 study conducted by Blau and Duncan (1967). The 1973 survey, executed in conjunction with the March 1973 Current Population Survey, represents approximately 53 million males in the civilian noninstitutional population between the ages of 20 and 65 in March 1973. Educational and labor force data were obtained from the March 1973 CPS household interviews; in about three fourths of the cases the CPS respondent was the spouse of the designated male. These data were supplemented in the fall of 1973 with social background and occupational career data from the mail-out, mail-back OCG questionnaire (OCGQ); in about three fourths of the cases the OCGQ respondent was the designated male. Responses to OCGQ were obtained from this questionnaire or subsequent telephone or personal follow-ups for more than 27,000 members of the experienced civilian labor force; the overall response rate was greater than 88 percent. A random subsample of about 1000 OCGQ respondents (600 nonblacks and 400 blacks) was selected for inclusion in the OCG remeasurement program (OCGR). Approximately three weeks after the mail return of their OCG questionnaires, telephone (and in a few cases personal) interviews were conducted with these respondents to obtain a second report of selected items on the OCG questionnaire.

Table 1 shows which variables were measured on each of the three occasions: CPS, OCGQ, and OCGR. Educational attainment (x_{43}), current (March) occupation (x_{63}), and age of the designated male (AGE) were ascertained in the March CPS interview. Reports of the three social background variables, father's (or other head of household's) occupation (x_{11}) and educational attainment (x_{21}) and parental family income (x_{31}), were obtained from the fall OCG questionnaire. Also, the fall questionnaire ascertained the man's first full-time, civilian job after completing schooling (x_{41}) and a second measurement of educational attainment (x_{51}). Thus, the CPS and OCGQ measurements provide two reports of educational attainment and one report of six other variables for each male in the full CPS-OCGQ sample. (The second measure ment of ED was not intended to supplant the CPS item, but rather to improve the respondent's recall of the timing of schooling and labor force entry.) Within the OCGR subsample, each of the variables except age was measured again. For technical reasons we were not able to ascertain March 1973 occupation in the OCGR interviews, and instead a report of current (Fall 1973) occupation (x_{62}) was obtained. While some job mobility occurred between the spring and fall surveys, we disregard it here on the argument that occupational status changes were negligible over the six or seven month period. Consequently, our estimates of unreliability in the reporting of current occupational status include effects of job mobility as well as response error. In summary, for OCGR respondents we have two measures of each of the social background variables (FO, FE, and PI), three reports of educational attainment (ED), two reports of both first and current occupation (O1 and OC), and a single report of age (AGE).

Each of the occupation reports was scaled using Duncan SEI scores for detailed 1960 Census occupation, industry, and class of worker categories (Duncan, 1961). Thus, our estimates of the quality of occupation reports do not pertain to description of occupations *per se*, but to a particular transformation of detailed job descriptions into a status metric (Featherman and Hauser, 1973). Educational attainment is coded in exact years of schooling completed, and parental income is coded as the logarithm of price adjusted dollars.[1] Age is expressed in years divided by ten, and a quadratic age variable, AGE2, is defined as $(\text{years}-40)^2/10$.

Model Specification

Our strategy is to specify and estimate a measurement model for the OCGR subsample, and then to apply the estimated measurement model to the full CPS-OCGQ sample. In this way we estimate substantive parameters in the full sample which have been corrected for response error. It is instructive to compare the corrected estimates with naive estimates for the full sample, i.e., estimates assuming perfect measurement. This paper reports our findings for nonblack men in the experienced civilian labor force. The pattern of measurement error for blacks is substantially more complex than the pattern for nonblacks. Comparisons of black and nonblack error structures and their implications for racial differences in the achievement process are presented in Bielby, Hauser, and Featherman (1976). There are 578 nonblacks in the remeasurement program subsample, and 25,201 nonblacks in the full sample.

Our structural model is presented in the path diagram of Figure 2.[2] The variables enclosed in boxes (FO, FE, PI, ED, O1, OC) are unobserved true scores. Linear and quadratic age terms (AGE and AGE2) are assumed to be measured without error in the CPS interviews. The term x_{ij} refers to the jth report of the ith variable, as indicated in Table 1.

The substantive portion of Figure 2 is a fully recursive model among true scores, represented by the following structural equations:

$$(3.1)\quad ED = \alpha_1 + \beta_1(AGE) + \beta_2(AGE2) + \beta_3(FO) + \beta_4(FE) + \beta_5(PI) + u_1,$$

$$(3.2)\quad O1 = \alpha_2 + \beta_6(AGE) + \beta_7(AGE2) + \beta_8(FO) + \beta_9(FE) + \beta_{10}(PI) + \beta_{11}(ED) + u_2,$$

$$(3.3)\quad OC = \alpha_3 + \beta_{12}(AGE) + \beta_{13}(AGE2) + \beta_{14}(FO) + \beta_{15}(FE) + \beta_{16}(PI) + \beta_{17}(ED) + \beta_{18}(O1) + u_3,$$

where the disturbances are independent of each other and of the explanatory variables in their respective equations. These substantive equations will be just-identified in terms of the true score variances and covariances; thus the fully recursive structure does not constrain estimates of parameters of the measurement model.

In algebraic form, the measurement portion of Figure 2 is:

$$(4.1a)\quad x_{11} = \lambda_{11}(FO) + e_{11},$$

$$(4.1b)\quad x_{12} = \lambda_{12}(FO) + e_{12},$$

$$(4.2a)\quad x_{21} = \lambda_{21}(FE) + e_{21},$$

$$(4.2b)\quad x_{22} = \lambda_{22}(FE) + e_{22},$$

$$(4.3a)\quad x_{31} = \lambda_{31}(PI) + e_{31},$$

$$(4.3b)\quad x_{32} = \lambda_{32}(PI) + e_{32},$$

$$(4.4a)\quad x_{41} = \lambda_{41}(ED) + e_{41},$$

$$(4.4b)\quad x_{42} = \lambda_{42}(ED) + e_{42},$$

$$(4.4c)\quad x_{43} = \lambda_{43}(ED) + e_{43},$$

$$(4.5a)\quad x_{51} = \lambda_{51}(O1) + e_{51},$$

$$(4.5b)\quad x_{52} = \lambda_{52}(O1) + e_{52},$$

$$(4.6a)\quad x_{62} = \lambda_{62}(OC) + e_{62},$$

$$(4.6b)\quad x_{63} = \lambda_{63}(OC) + e_{63}.$$

The model allows both within-occasion and within-variable correlated response error. Response errors of reports obtained from the Fall OCG questionnaire (e_{11}, e_{21}, e_{31}, e_{41} and e_{51}) may be intercorrelated, as may be errors of reports obtained from the Fall OCG telephone reinterview (e_{12}, e_{22}, e_{32}, e_{42}, e_{52}, and e_{62}) and the errors of the two reports obtained from the March CPS household interview (e_{43} and e_{63}). We allow within-variable correlated errors in the reports of variables obtained from the Fall OCG questionnaire and the Fall OCG telephone reinterview, that is, correlations between e_{i1} and e_{i2} for $i = 1,\ldots,5$. It seems plausible that recall contamination might occur in these responses obtained, on the average, about 24 days apart. However, we assume that such contamination does not occur between March CPS reports and Fall OCG reports of educational attainment and occupational status; these were obtained more than five months apart and usually from different respondents.

We establish a metric for the true scores by fixing $\lambda_{11} = \lambda_{21} = \lambda_{31} = \lambda_{43} = \lambda_{51} = \lambda_{63} = 1.0$. That is, we fix the metric of the true scores to be the same as that of the observed reports which are used in models for the full CPS-OCGQ sample: the metrics of FO, FE, PI, and O1 are identical to those of the corresponding OCGQ reports, and the CPS reports define the metrics for ED and OC. Normalization of this kind is necessary because the metric of an unobserved variable is arbitrary, and consequently the slope coefficients with respect to indicators are identifiable only relative to each other. For example, given our normalization, a coefficient λ_{i2} greater (smaller) than unity indicates a conditional expectation slope of the OCGR report on the corresponding true score which is steeper (flatter) than the slope of the OCGQ report on the true score. However, the absolute values of the two slopes are indeterminate.[3] This normalization is imposed on all of our models.

Our measurement models are all based on equation 4 and differ only in the specification of the covariances among the e_{ij} and the restrictions imposed upon the λ_{ij}. Our most restrictive specification, Model A, permits only random measurement errors, so the e_{ij} are assumed to be mutually uncorrelated. It corresponds to the random measurement error models of Siegel and Hodge (1968: 51-52), Jencks et al., (1972: 330-336), Treiman and Hauser (1976), and the one implicitly used by other researchers applying "corrections for attenuation" (cf. Bohrnstedt, 1970). Thus, in Model A the 91 variances and covariances among the thirteen reports (ignoring age) are to be reproduced by 41 free parameters: 7 slope coefficients, 13 error variances, 6 true score variances, and 15 true score covariances.

After assessing Model A, we consider more complex measurement models. Model B corresponds to the model specified by Bowles (1972). It differs from Model A only in that within-variable error correlations ($\rho_{e_{i1},e_{i2}}$ for i = 1,...,5) are fixed to be 0.5 instead of fixed to be zero. Model C allows both within-variable and within-occasion error correlations. To identify these additional parameters, we must impose some other constraints. We constrain the within-variable error correlations to be equal across the five variables measured both in the OCG questionnaire and the remeasurement interviews:

$$\rho_{e_{11}e_{12}} = \rho_{e_{21}e_{22}} = \ldots = \rho_{e_{51}e_{52}}.$$

Within-occasion correlated errors are constrained to be equal when they involve the same pair of variables. That is, we have 10 constraints of the form

$$\rho_{e_{i1}e_{k1}} = \rho_{e_{i2}e_{k2}} \quad (i, k = 1,\ldots,5;\ i \neq k)$$

and, also,

$$\rho_{e_{43}e_{63}} = \rho_{e_{42}e_{62}}.$$

The other four within-occasion correlated errors, $\rho_{e_{i2}e_{62}}$ (i - 1,2,3,5) are unconstrained. Model C adds 16 free parameters for the measurement error correlations: one for the within-variable correlation, and 15 for the within-occasion correlations.

We estimate other models but these are variations of Models A, B, and C. Then we take the most appropriate or best fitting model, and re-estimate it after eliminating statistically and substantively insignificant coefficients and constraining to unity those estimated slope coefficients which appear statistically indistinguishable from 1.0.

The measurement model parameter estimates for the OCGR subpopulation provide a true score variance-covariance matrix from which we could solve for the substantive parameters of equations 3. However, we can obtain more stable estimates of the substantive parameters by using the measurement error variances and error correlations from the OCGR subpopulation to correct the observed variance-covariance matrix for the full CPS-OCGQ sample. In doing so, we assume that our OCGR-based estimates of of equations 4.1a, 4.2a, 4.3a, 4.4c, 4.5a, and 4.6b apply to the CPS reports of ED and OC and OCGQ reports of FO, FE, PI, and 01 in the full CPS-OCGQ sample.[4] We can than compare substantive parameters estimated from the corrected and uncorrected full sample variance-covariance matrices.[5]

Estimation of Measurement Models

Assuming the joint distribution of the thirteen reports of status variables is multivariate normal, we obtain maximum likelihood estimates of parameters of the 13-equation measurement model using Jöreskog's (1970) "general method for the analysis of covariance structures." The estimates have been computed from pairwise present correlations for non-black males 20 to 65 years old in the experienced civilian labor force in March 1973.[6] The correlations among the thirteen reports are given in Table 2 and means and standard deviations appear in the first two columns of Table 3. There is a slight tendency for respondents to report higher statuses in the remeasurement telephone interviews for three variables, FO, PI, and ED. While this may indicate a social desirability effect in the interview situation which is not elicited by the questionnaire (Couch and Keniston, 1960; Campbell, et al., 1967), it may be due in part to lower response rates for some items among lower status persons in the telephone interview. There is a more pronounced tendency for the OCGQ items to vary less than the same OCGQ items. Thus, we might expect to find smaller error variances in the OCGR items.

Goodness-of-fit tests for the various measurement models are reported in Table 4. The likelihood-ratio test statistic contrasts the null hypothesis that constraints on the observed variance-covariance matrix are satisfied in the population with the alternative that the variance-covariance matrix is unrestricted. In large samples this statistic has a chi-square distribution with degrees of freedom equal to the difference between the number of variances and covariances and the number of independent parameters estimated under the hypothesized model. Moreover, when two measurement models are "nested," that is, when one model can be obtained by constraining the parameters of a more general model, the difference in chi-square values provides a likelihood-ratio test of the constrained parameters.

Model A, the random measurement error model, fits remarkably well ($p= .718$). In contrast, the "Bowles" model, Model B, differing only in that within-variable correlated error is fixed at 0.5 instead of zero, provides a much worse fit ($p= .003$). Model C adds the 16 parameters for within-occasion and within-variable correlated error to the random measurement error model, but the fit does not significantly improve over Model A. The difference in chi-square values of 12.8 with 16 degrees of freedom is not statistically significant (compare lines A and C). Lines D and E of Table 4, respectively pertain to models with within-occasion correlated error, but not within-variable correlated error, and _vice versa_. Contrasting line D with line C, we see that the chi-square value for the within-variable correlated error parameter is not statistically significant. Comparing lines E and C, the chi-square value for the within-occasion correlated error parameters is 12.22 with 15 degrees of freedom, which is again less than its expected value on the null hypothesis. The point estimate of within-variable correlated error is 0.1 with an approximate standard error of 0.1 (not shown in the table). The largest point estimate of within-occasion correlated error is 0.07 with an approximate standard error of 0.07. Thus, neither in a global test, in separate tests for within-occasion and within-variable error correlations, nor in our examination of the several estimated within-occasion error correlations, do we find substantial evidence of correlated error.

The evidence that reporting errors are random for nonblack men is almost, but not quite, complete. Model F, the final measurement model, was constructed by imposing unit slopes on those free λ_{ij} which were within approximately one standard error of 1.0. Under Model A there were 7 free slope parameters (λ_{ij}), but only the estimates of λ_{62}, λ_{41}, and λ_{42} were significantly different from 1.0. Further, the latter two estimated did not differ significantly from one another. Thus, in Model F we estimate only 2 free nonunit slope parameters, $\lambda_{41} = \lambda_{42}$ and λ_{62}. The five additional constraints in Model F raise chi-square by only 1.45 relative to Model A, and thus the 36 free parameters of Model F (2 slope coefficients, 13 error variances, 6 true-score variances, 15 true score covariances) provide a quite good representation of the 91 variances and covariances of the observed reports (χ^2 = 45.27 with 55 df; p = .822).

Parameter estimates for this final measurement model appear in columns 3 through 5 of Table 3. Several features of these estimates are noteworthy. The OCGR reports uniformly have smaller error variances than the OCGQ reports. The three variables measured in the Duncan SEI metric (FO, 01, and OC) have error standard deviations ranging from 8 to 12, with those for FO and 01 somewhat smaller than those for OC. It may be that the retrospective reports are less detailed, or that respondents are ignoring transient components of their fathers', and their own first, occupations which are not ignored in describing their own current occupations. The error standard deviation of the OCGQ report of educational attainment is anomalously large, nearly three times that obtained with the same item in the OCGR telephone interview.

As noted above, only two slope coefficients depart from the normalized value of 1.0. The CPS household interview report of educational attainment has a flatter slope than the other two reports, while the CPS report of occupational status has a steeper slope than the OCGR telephone interview report. Reliability coefficients (the squared true score-observed score correlations estimated from the measurement model) appear in column 6. It is striking that retrospective reports of social background variables are no less accurate than contemporaneous reports of status variables.

Correlations between the first and second reports of each of the variables appear in column 7. These observed "test-retest" correlations correspond to the reliability coefficients that would be obtained under a classical test theory model with congeneric forms in the measurement of each variable. For most variables these correlations are close to the mean of the estimated reliability coefficients of the indicators presented in column 6.

Column 8 presents external evidence of data quality: correlations between two independent codings of the OCGQ questionnaire responses for the variables FO, FE, PI, ED and O1. (The Bureau of the Census recoded OCG questionnaire responses after they were transcribed to telephone interview forms. Telephone interviewers used the transcribed responses to reconcile discrepancies after a second report was obtained.) These correlations reflect unreliability due to transcription, coding and keypunching error, but are free of unreliability due to response error. Thus, they provide an upper bound to the reliabilities attainable from the

OCG questionnaire. We find very little coding unreliability in the precoded FE and PI variables. The coding reliability is .94 for FO and O1, which were coded into detailed Census codes from questions on occupation, industry, and class of worker and then transformed into the status metric. The correlation between codings of the education item in the OCG questionnaire is an unusually low .95. Thus, the relatively high error variance of the OCG questionnaire report of education may be due to unusually high coding or keypunch errors for that item.

Estimation of Substantive Parameters in the Full CPS-OCGQ Sample

In this section we assess the effects of measurement error on substantive interpretations of the achievement process. Tables 5 and 6 present observed (uncorrected) and corrected correlations, means, and standard deviations for nonblacks in the full CPS-OCGQ sample. Comparisons of means and standard deviations with corresponding quantities in the remeasurement program subsample reveal no large or systematic biases in the composition of the subsample.

Table 7 presents corrected estimates of structural and reduced form parameters. Metric and standardized coefficients are presented for the structural equations (lines 1, 3, and 6) and reduced form equations (lines 1, 2, 4 and 5) of our recursive model. The model is now overidentified because certain coefficients are constrained to equal zero in the structural equations. The constrained coefficients are effects of father's education and parental income on first and current occupation net of schooling, which were originally estimated to be quite small and in some cases (implausibly) negative.[7]

In Table 7 the reduced form equations (1, 2, and 4) reveal that the background variables (FO, FE, and PI) all affect each aspect of socio-economic achievement. Together with the age variables, they account for about two-fifths of the variance in educational attainment and more than one fourth of the variance in statuses of first and current occupations. The standardized reduced form coefficients reveal that parental income (PI) has the strongest relative impact on educational attainment (ED), while father's occupational status (FO) has the largest effect on the two occupational statuses (01 and OC).

Educational attainment (ED) completely mediates net advantages in occupational status due to FE and PI (compare equations 2 with 3 and 4 with 5). That is, educational advantages (or disadvantages) account for the influence of father's education and parental income on a man's occupational standing. In contrast, the effect of father's occupational status on schooling accounts for less than half of its influence on the status of son's first or current occupation. The direct influence of father's occupational status (FO) on son's status is about a fifth of an SEI point for each point of FO in the 01 equation (3) and about a seventh of a point for each point of FO in the OC equation (5). The effects of a year of schooling are about 5.2 SEI points in status of first job and about 4.9 SEI points in status of 1973 job. Adding educational attainment nearly doubles the proportion of variance explained (R^2) in both the 01 and OC equations.

Entering status of first job into the equation for current occupational status reduces the effect of educational attainment on current occupational status by a factor of one half (compare equations 5 and 6). That is, about half the effect of schooling on current occupational standing reflects the payoff to schooling in selection of the first job, but schooling also directly affects one's standing later in the occupational career. The stability of occupational status is about one half SEI point of current status for each SEI point of first job status. None of the social background factors appears to affect current occupational standing except by way of schooling and first jobs. Overall, background and educational attainment account for about 60 percent of the variance in status of first job and about 50 percent of the variance in status of current job.

Table 8 presents an analogous set of estimated coefficients which are based on direct application of least squares to the observed full CPS-OCGQ sample moments, ignoring response error. First we compare the variation in each dependent variable in Tables 7 and 8. The confounding of measurement error with true variation results in a 5 percent overstatement of the total variation, σ_t, in educational attainment and a 9 percent overstatement of the variation in first and current job status. Residual variation, σ_u, which includes measurement errors in the dependent variables in Table 8, is overestimated by 10 percent in the ED equation and 15 to 27 percent in the 01 and OC equations. Explained variation in the dependent variables, $\sigma_{\hat{t}}$, is underestimated by 3 to 8 percent in each equation in Table 8. Thus, if we ignore measurement error, we slightly overstate the total amount of socioeconomic inequality and we slightly understate the inequality which is attributable to variation in socioeconomic background and educational attainment. The naive estimates substantially overestimate the amount of unexplained, or conditional, socioeconomic inequality. In all there is a 15 percent underestimate of the proportion of variance explained (R^2) in ED, and there are 23 to 29 percent underestimates of the proportions of variance explained in O1 and OC.

The estimated effects of paternal education (FE) are almost unaffected by correction for measurement error, but there appear to be substantial downward biases in the estimated reduced form coefficients of the other social background variables. The reduced form effects of father's occupational status (FO) are underestimated 12 to 16 percent and those of parental income (PI) are underestimated 10 to 19 percent. Father's occupational status is the only social background variable to have nontrivial effects on first and current job status net of education (equations 3 and 5), and the estimates of these effects are barely affected by measurement error.

The uncorrected estimates understate the effect of a year of schooling (ED) on status of first job (O1) by 10 percent. The schooling coefficient is biased by about the same amount in the case of current occupational status (equations 5 in Tables 7 and 8). In equation 6, the effect of status of first job on current occupational status is underestimated by 22 percent, while the effect of schooling is overestimated by 11 percent.

To summarize, ignoring measurement errors in models for nonblacks males results in modest biases (10 to 19 percent) in the reduced form effects of two of the three background variables: father's occupational status and parental family income. That is, we understate the effects of these two variables on educational attainment and their effects on first and current job status as transmitted by years of schooling. Though not to the same degree, measurement error also reduces estimated returns to schooling net of social background. Note that downward bias in the schooling coefficient contributes to the downward bias in the reduced form effects of background variables. The largest single difference between the corrected and uncorrected structural coefficients involves neither status inheritance nor returns to schooling, but is a substantial (22 percent) downward bias in stability of occupational status within the son's career. The other major difference between the corrected and uncorrected models is the overstatement in the latter model of the degree to which variation in socioeconomic achievements is not determined by social background and education. After the effects of schooling and social background are taken into account, about a quarter of the remaining variation, which is sometimes ascribed to luck or chance, is actually random response error.

Conclusion

Several sociologists and economists have noted possible biases in effects of social background and schooling when intergenerational models of the achievement process are based on retrospective survey reports of status variables. The prevailing view has been that effects of social background are biased downward by errors in retrospective reports; consequently, effects of schooling are biased upward, at least relative to those of social background. But research on these biases has been inconclusive because appropriate data and statistical models have not been available. Using data from the remeasurement program of the 1973 Occupational Changes in a Generation Survey, we have overcome some of these shortcomings by estimating and testing comprehensive structural models which incorporate both random and nonramdon response errors.

We think there is persuasive evidence that reports of social background and achievement variables by nonblacks are subject only to random response error. Moreover, we find no evidence that social background variables are measured substantially less reliably than are contemporaneous achievement variables. Contrary to some previous expectations, response error leads to downward biases in estimated returns to schooling, and downward biases in estimated effects of social background variables are neither pervasive nor very large. Ignoring response error, we underestimate occupational returns to schooling by about 10 percent and the effects of father's occupational status and parental income on son's statuses by as much as 19 percent. Yet downward biases in estimated effects of father's educational attainment are negligible. Measurement error does have a substantial effect on estimates of status persistence within the occupational career. Also, by ignoring response errors, we overstate the total amount of variation in achievement variables by 5 to 9 percent, and we overstate the variation in achievement variables which is independent of social background by 10 to 16 percent.

We think that our research has produced new and powerful evidence about the effects of survey response errors on models of the stratification process. However, a cautionary note is in order. Our data were collected as part of a carefully designed and instrumented study which uses the resources, personnel, and procedures of the United States Bureau of the Census. It may be inappropriate to apply our estimates of measurement parameters to data obtained using instruments and procedures which differ from those of the OCG-II survey. Further, the present results apply only to nonblack males. We have no data for females, and research we have reported elsewhere (Bielby, Hauser and Featherman, 1976) suggests that survey response errors among black males differ in pattern and in magnitude from those among nonblack males.

NOTES

[1]The OCG parental income item was: "When you were about 16 years old, what was your family's annual income?" The fourteen possible responses were:

No income (or loss),
$1-499,
$500-999,
$1,000-1,999,
$2,000-2,999,
$3,000-3,999,
$4,000-4,999,
$5,000-5,999,
$6,000-6,999,
$7,000-7,999,
$8,000-8,999,
$9,000-9.999.
$10,000-14,999
$15,000 or more

After examining plots of occupational status of first and current job and educational attainment by parental income category we determined that a logarithmic function of parental income was the appropriate functional form relating it to the achievement variables. The first two categories were collapsed and midpoints of intervals were used. A value of $19,750 was assigned to the open-ended category on the basis of a canonical analysis with ED, O1 and OC as criterion variables. Responses to pretest probes and plots of achievement variables by parental income categories by ten-year age cohorts clearly indicated that respondents tended not to adjust their responses to current dollars. Therefore, the dollar midpoint responses were adjusted by a four-year moving average of the Consumer Price Index, with the four years weighted to reflect the uncertainty in determining exact year of birth from age in March 1973.

The final scale was computed as the logarithm (base 10) of the price adjusted dollar category midpoints. Our scaling procedure explicitly attempted to maximize correlations between parental income and statuses of the respondent. As a consequence, intergenerational (father-son) correlations between PI and ED are larger than intragenerational (father's generation) correlations between PI and both FO and FE (see Tables 2, 5 and 6).

[2]Figure 2 shows the most general (least restricted) model which we estimated. Ultimately, we eliminated all correlations among reporting errors and certain paths from background variables to occupational statuses.

[3]Another way of stating this normalization is that only the ratio of the slopes is identifiable. A more common normalization is to assume unit variances of true scores. However, this normalization does not allow the computation of metric coefficients relating unobservables. Error variances and reliabilities (squared true score-observed score correlations) are invariant with respect to normalization, although true score variances (and structural coefficients) do depend on which λ_{ij} are fixed to unity.

[4]Again we have an indeterminacy in the slope of the conditional expectation function of the observed score given true score, and we assume that the measures included in the full sample models define the true score metrics. That is, in our models for the full CPS-OCGQ sample we assume all such slopes to be unity. Since all of our metrices, except

perhaps that of educational attainment, are to some degree arbitrary, it seems reasonable to normalize by taking the observed metrics as the standard. While our findings do suggest some relative differences in slope coefficients, there is no empirical way to choose which slope coefficients correspond to "true" metrics.

[5] Since the mean vector is not restricted by the model, the sample means provide the maximum likelihood estimates of the true score means.

[6] The Bureau of the Census uses the "hot deck" technique to allocate nonresponses in CPS reports of education and occupation, and we treat these allocations as responses. Allocated nonresponses are assigned the observed value of the last case processed with the same age, sex and race. Thus, allocated responses have both systematic and random components. Elsewhere, of course, we assume that the pairwise correlations accurately represent the correlations that would have been obtained were complete data available. While this is an untestable assumption, the alternatives are more problematic. Replacement with means restricts variances and would result in underestimates of error variances. Random allocation would reduce the ability to detect nonrandom response error structure, while systematic allocation would have the opposite effect. Omitting all cases that have missing data would reduce the sample size by about 40 percent and probably eliminate many of the cases with less accurate responses. Models of the achievement process are almost always estimated from pairwise present correlations, and it is the response error structure in these analyses that we are attempting to assess.

[7]Using the LISREL program of Jöreskog and van Thillo (1972), we estimated structural and measurement parameters simultaneously within the OCGR subsample. The estimated measurement parameters of Model F were virtually unaffected by the constraints $\beta_9 = \beta_{10} = \beta_{15} = \beta_{16} = 0$ (see equations 3.2 and 3.3). These four restrictions raised the chi-square in the LISREL model from 58.5 with 69 df to 66.7 with 73 df, an increase not statistically significant at the .05 level. (The degrees of freedom and chi-square values differ from those in Table 4 because AGE and AGE2 were included in the LISREL model; estimated measurement parameters were unaffected by inclusion of the two age variables.) With this evidence in hand we dropped the negligible paths and estimated the structural coefficients in the full sample by least squares regression Reduced form coefficients were obtained algebraically from the structural equations.

REFERENCES

Bielby, William T., Robert M. Hauser and David L. Featherman

1976 "Response errors of black and nonblack males in models of status inheritance and mobility." Paper prepared for presentation at the August, 1976 meetings of the American Sociological Association, New York.

Blau, Peter M. and Otis Dudley Duncan

1967 The American Occupational Structure. New York: Wiley.

Bohrnstedt, George W.

1970 "Reliability and validity assessment in attitude measurement."
Pp. 80-99 in Gene F. Summers (ed.), Attitude Measurement. Chicago: Rand McNally.

Bowles, Samuel

1972 "Schooling and inequality from generation to generation." Journal of Political Economy 80 (May/June): S219-S251.

Bowles, Samuel and Valerie I. Nelson

1974 "The 'inheritance of IQ' and the intergenerational reproduction of economic inequality." Review of Economics and Statistics 56 (February): 39-51.

Campbell, Donald T., Carole R. Seigman and Matilda B. Rees

1967 "Direction-of-wording effects in the relationships between scales." Psychological Bulletin 68 (November): 292-303.

Couch, A. and K. Keniston

1960 "Yeasayers and naysayers: agreeing response set as a personality variable." Journal of Abnormal and Social Psychology 60: 151-174.

Duncan, Otis Dudley

1961 "A socioeconomic index for all occupations." Pp. 109-138 in Albert J. Reiss, Jr., Occupations and Social Status. New York: Free Press.

Duncan, Otis Dudley, David L. Featherman and Beverly Duncan

1972 Socioeconomic Background and Achievement. New York: Seminar Press.

Featherman, David L.

1972 "Achievement orientations and socioeconomic career attainments." American Sociological Review 37 (April): 131-143.

Featherman, David L. and Robert M. Hauser

1973 "On the measurement of occupation in social surveys." Sociological Methods and Research 2 (November): 239-251.

Jencks, Christopher, Marshall Smith, Henry Acland, Mary Jo Bane, David Cohen, Herbert Gintis, Barbara Heyns and Stephan Michelson

1972 Inequality. New York: Basic Books.

Jöreskog, Karl G.

1970 "A general method for the analysis of covariance structures." Biometrika 57 (August): 239-251.

Jöreskog, Karl G., Gunnar T. Gruvaeus and Marielle van Thillo

1970 "ACOVS: a general computer program for analysis of covariance structures." Research Bulletin 70-15, Educational Testing Service, Princeton, New Jersey.

1972 "LISREL: A general computer program for estimating a linear structural equation system involving multiple indicators of unmeasured variables." Research Bulletin 72-56, Educational Testing Service, Princeton, New Jersey.

Kelley, Jonathan

1973 "Causal chain models for the socioeconomic career." American Sociological Review 37 (August): 481-493.

Mason, William M., Robert M. Hauser, Alan C. Kerckhoff, Sharon Sandomirsky Poss and Kenneth Manton

1976 "Models of response error in student reports of parental socioeconomic characteristics." Pp. 443-494 in William H. Sewell, Robert M. Hauser and David L. Featherman (eds.), Schooling and Achievement in American Society, New York: Academic Press.

Sewell, William H. and Robert M. Hauser

1975 Education, Occupation and Earnings: Achievement in the Early Career. New York: Academic Press.

Siegel, Paul M. and Robert W. Hodge

1968 "A causal approach to the study of measurement error." Pp. 28-59 in Hubert M. Blalock and Ann B. Blalock (eds.), Methodology in Social Research. New York: McGraw-Hill.

Treiman, Donald J. and Robert M. Hauser

1976 "The intergenerational transmission of income." Forthcoming in Robert M. Hauser and David L. Featherman, The Process of Stratification: Trends and Analyses. New York: Academic Press.

Wiley, David E. and James A. Wiley

1970 "The estimation of measurement error in panel data." *American Sociological Review* 35 (February): 112-117.

TABLE 1. Timing of measurements in the 1973 CPS and OCG surveys.

Variable	Measurement: March 1973 CPS household interview (CPS)	Fall 1973 OCG questionnaire (OCGQ)	Fall 1973 OCG remeasurement interview (OCGR)
1. Father's occupational status (FO)	-	x_{11}	x_{12}
2. Father's educational attainment (FE)	-	x_{21}	x_{22}
3. Parental income (PI)	-	x_{31}	x_{32}
4. Educational attainment (ED)	x_{43}	x_{41}	x_{42}
5. Occupational status of first job after completing schooling (O1)	-	x_{51}	x_{52}
6. Current occupational status (March or fall) (OC)	x_{63}	-	x_{62}
7. Age	AGE, AGE2	-	-

TABLE 2. Observed correlations among status variables: OCGR subsample of nonblack males in the experienced civilian labor force, March 1973 (N = 578)

Variable			(1)		(2)		(3)		(4)			(5)		(6)	
			x_{11}	x_{12}	x_{21}	x_{22}	x_{31}	x_{32}	x_{41}	x_{42}	x_{43}	x_{51}	x_{52}	x_{62}	x_{63}
1.	FO	x_{11}	--												
		x_{12}	.869	--											
2.	FE	x_{21}	.585	.589	--										
		x_{22}	.597	.599	.939	--									
3.	PI	x_{31}	.422	.437	.477	.467	--								
		x_{32}	.426	.450	.486	.478	.913	--							
4.	ED	x_{41}	.428	.430	.448	.445	.426	.439	--						
		x_{42}	.445	.443	.483	.492	.485	.502	.838	--					
		x_{43}	.419	.419	.467	.467	.486	.501	.801	.921	--				
5.	O1	x_{51}	.398	.410	.290	.300	.370	.358	.581	.644	.637	--			
		x_{52}	.409	.409	.325	.322	.363	.348	.578	.642	.631	.847	--		
6.	OC	x_{62}	.340	.369	.280	.284	.291	.296	.504	.563	.534	.585	.599	--	
		x_{63}	.364	.390	.291	.308	.307	.301	.519	.603	.566	.618	.620	.797	--

NOTE: See Table 1 for definitions of variables.

TABLE 3. Observed moments and measurement model parameter estimates: nonblack males in the experienced civilian labor force, March 1973 (N = 578)

Variable		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
True T_i	Observed x_{ij}	Mean μ_{ij}	Std. dev. $\sigma_{x_{ij}}$	Std. dev. of Error[a] $\sigma_{e_{ij}}$	Std. dev. of True Score σ_{T_i}	Relative Slope[a] λ_{ij}	Reliability Coefficient[b] $(\sigma^2_{T_i}/\sigma^2_{x_{ij}})\lambda^2_{ij}$	Test-retest Correlations $\rho_{x_{i1},x_{i2}}$	Coding Reliability $\rho_{x_{i1},x_{i1'}}$	No. of Cases
FO	x_{11}	32.96	24.27	9.37 (.54)	22.37	1.00	.85	.87	.94	556
	x_{12}	33.62	23.73	7.97 (.59)		1.00	.89			551
FE	x_{21}	8.97	4.19	1.12 (.09)	4.04	1.00	.93	.94	.99	548
	x_{22}	8.96	4.14	0.93 (.10)		1.00	.95			541
PI	x_{31}	3.78	0.41	0.14 (.01)	0.38	1.00	.86	.91	.99	517
	x_{32}	3.81	0.39	0.09 (.01)		1.00	.95			520
ED	x_{41}	11.98	3.42	1.78 (.06)		1.06 (.02)	.70	.84[c]	.95	535
	x_{42}	12.12	2.93	0.61 (.06)	2.71	1.06 (.02)	.96			545
	x_{43}	12.18	2.87	0.97 (.04)		1.00	.89			578[e]
O1	x_{51}	34.61	24.71	9.86 (.52)	22.47	1.00	.87	.85	.94	514
	x_{52}	32.10	24.15	9.26 (.54)		1.00	.87			541
OC	x_{62}	39.57	24.81	12.25 (.65)	23.11	0.93 (.04)	.76	.80[d]	--	578[e]
	x_{63}	41.34	25.21	10.08 (.80)		1.00	.84			578[e]

[a] Standard errors of parameter estimates appear in parentheses.

[b] These coefficients are squared "validity coefficients." They have approximate standard errors on the order of 0.03.

[c] $\rho_{x_{41},x_{43}} = .80$, $\rho_{x_{42},x_{43}} = .92$.

[d] This quantity is $\rho_{x_{62},x_{63}}$, the correlation between SEI scores of reports of March 1973 occupation and Fall 1973 occupation.

[e] Missing values have been allocated for NA cases.

TABLE 4. Chi-square goodness-of-fit tests for measurement models: nonblack males in the experienced civilian labor force, March 1973.[a]

Model	χ^2	df	p
A. Random Measurement Error--No Constrained Slopes	43.82	50	.718
B. "Bowles" Model--Within-Variable Correlated Error Fixed at 0.5	81.61	50	.003
C. Within-Occasion and Within-Variable Correlated Error	31.06	34	.612
D. Within-Occasion Correlated Error	31.95	35	.616
E. Within-Variable Correlated Error	43.28	49	.703
F. Random Measurement Error--Constrained Slopes	45.27	55	.822

[a]Maximum likelihood estimates were computed with the ACOVSF program described in Jöreskog, Gruvaeus and van Thillo (1970).

TABLE 5. Uncorrected correlations, means, and standard deviations: CPS-OCGQ nonblack males in the experienced civilian labor force, March 1973 (N = 25,223).[a]

Variable	1	2	3	4	5	6	7	8
1. x_{11}	--							
2. x_{21}	.537	--						
3. x_{31}	.400	.466	--					
4. x_{43}	.411	.470	.483	--				
5. x_{51}	.392	.330	.293	.636	--			
6. x_{63}	.326	.275	.257	.571	.617	--		
7. AGE	-.174	-.297	-.248	-.210	-.067	.025	--	
8. AGE2	.014	.026	-.027	-.095	-.114	-.142	.144	--
Mean	31.09	8.78	3.77	12.07	33.81	41.11	3.97	16.04
Std. dev.	22.90	4.04	0.42	3.07	24.55	24.91	1.25	14.63

[a]See Table 1 for definitions of variables.

TABLE 6. Corrected correlations, means, and standard deviations: CPS-OCGQ nonblack males in the experienced civilian labor force, March 1973 (N = 25,223).[a]

Variable	1	2	3	4	5	6	7	8
1. FO	--							
2. FE	.612	--						
3. PI	.464	.514	--					
4. ED	.475	.516	.539	--				
5. O1	.469	.375	.339	.732	--			
6. OC	.391	.313	.298	.658	.737	--		
7. AGE	-.191	-.309	-.264	-.221	-.073	.027	--	
8. AGE2	.015	.003	-.028	-.100	-.124	-.155	.144	--
Mean	31.09	8.78	3.77	12.07	33.81	41.11	3.97	16.04
Std. dev.	20.90	3.88	0.40	2.91	22.48	22.78	1.25	14.63

[a]See Table 1 for definitions of variables.

TABLE 7. Corrected estimates of parameters of the achievement process: nonblack males in the experienced civilian labor force, March 1973 (N = 25,223)[a,b]

Dependent Variable	Predetermined Variables							R^2	Components of Variation[c]		
	AGE	AGE2	FO	FE	PI	ED	O1		Residual σ_u	Explained $\sigma_{\hat{t}}$	Total σ_t
1. ED	−.034	−.018	.025	.175	2.42	--	--	.395	2.27	1.83	2.91
	(−.014)	(−.092)	(.178)	(.233)	(.330)						
2. O1	1.96	−.211	.318	.901	12.46	--	--	.303	18.77	12.37	22.48
	(.110)	(−.138)	(.295)	(.155)	(.220)						
3. O1	2.14	−.118	.189	--	--	5.15	--	.572	14.71	17.00	22.48
	(.119)	(−.077)	(.176)			(.667)					
4. OC	3.65	−.282	.270	.859	11.88	--	--	.253	19.69	11.46	22.78
	(.201)	(−.182)	(.247)	(.146)	(.207)						
5. OC	3.82	−.194	.147	--	--	4.91	--	.491	16.25	15.96	22.78
	(.209)	(−.124)	(.135)			(.628)					
6. OC	2.73	−.134	.051	--	--	2.30	.507	.598	14.44	17.62	22.78
	(.150)	(−.086)	(.047)			(.294)	(.500)				

[a]Standardized coefficients appear in parentheses.

[b]Estimates of measurement error variances are based on a subsample of 578 observations.

[c]Components are expressed as standard deviations. The additive decomposition is $\sigma_t^2 = \sigma_{\hat{t}}^2 + \sigma_u^2$.

TABLE 8. Uncorrected estimates of parameters of the achievement process: nonblack males in the experienced civilian labor force, March 1973 (N = 25,223)[a]

Dependent Variable	Predetermined Variables							R^2	Components of Variation[b]		
	AGE	AGE2	FO	FE	PI	ED	O1		Residual σ_u	Explained $\sigma_{\hat{t}}$	Total σ_t
1. ED	-.058	-.019	.021	.183	2.18	--	--	.337	2.50	1.78	3.07
	(-.024)	(-.092)	(.160)	(.241)	(.299)						
2. O1	1.60	-.214	.281	.845	10.07	--	--	.216	21.74	11.41	24.55
	(.081)	(-.128)	(.264)	(.139)	(.173)						
3. O1	1.87	-.126	.184	--	--	4.62	--	.437	18.42	16.23	24.55
	(.095)	(-.075)	(.172)			(.578)					
4. OC	3.32	-.285	.241	.804	9.58	--	--	.180	22.56	10.57	24.91
	(.167)	(-.168)	(.223)	(.131)	(.162)						
5. OC	3.58	-.201	.148	--	--	4.39	--	.375	19.69	15.25	24.91
	(.179)	(-.118)	(.136)			(.541)					
6. OC	2.84	-.152	.076	--	--	2.58	.393	.459	18.32	16.88	24.91
	(.143)	(-.089)	(.070)			(.318)	(.387)				

[a]Standardized coefficients appear in parentheses.

[b]Components are expressed as standard deviations. The additive decomposition is $\sigma_t^2 = \sigma_{\hat{t}}^2 + \sigma_u^2$.

Figure 1: A Fully Recursive Structural Equation Model with Measurement Errors

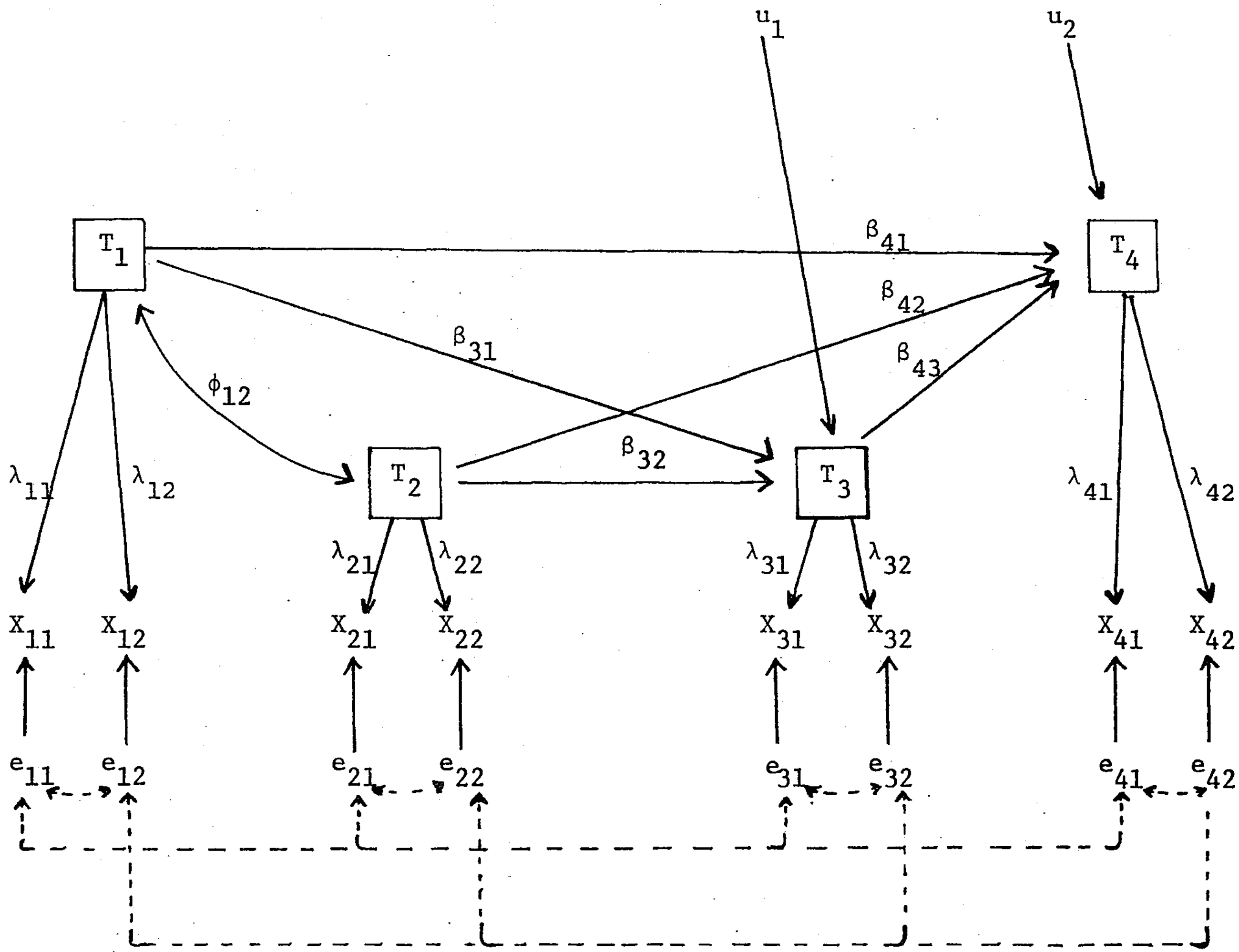
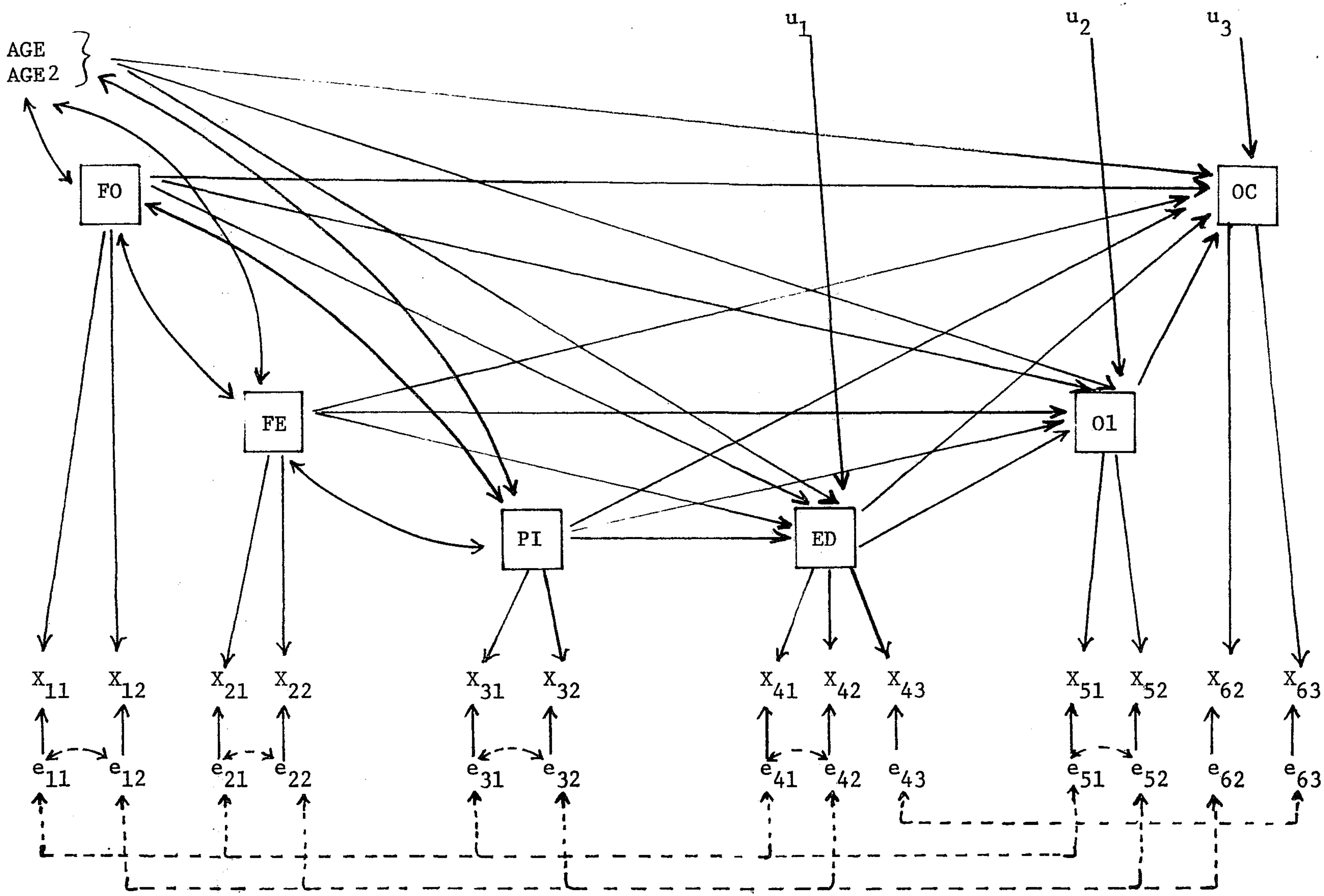


Figure 2: A Structural Equation Model of the Socioeconomic Achievement Process with Measurement Errors



NOTE: Variables are defined in Table 1.