This article presents structural equation models with discrete dependent variables that refer to occupational destinations. After assuming threshold measurement models and structural models with normally distributed error terms, it is shown that the linear relationships among observed and latent continuous variables can be treated in a way that is similar to conventional structural equation models in the LISREL framework. The models that are presented are simple cases of a large class of models that can be estimated with the computer program LISCOMP. Reanalyzing data from the 1962 Occupational Changes in a Generation Survey, the models incorporate discrete occupational destinations into the classic Blau-Duncan model. Results indicate that although the likelihood of becoming a manager, official, or proprietor is directly affected by parental social status, the chances of becoming a scientist or engineer are affected only indirectly through education.

Structural Equation Models for Ordinal Variables

An Analysis of Occupational Destination

YU XIE
University of Wisconsin–Madison

In sociological research, discrete dependent variables are frequently encountered. Occupational destination, crime commission, marital status, educational transition, employment status, and military enlistment are a few examples. Although the theoretical foundations needed to analyze discrete dependent variables in the framework of structural equations have been laid (Heckman, 1978; Muthén, 1979, 1983, 1984; Winship and Mare, 1983), sociologists

AUTHOR'S NOTE: *Computations were performed at the Center for Demography and Ecology and Madison Academic Computing Center, University of Wisconsin-Madison. The author is grateful to Meichu Chen, Robert M. Hauser, J. Scott Long, Robert D. Mare, Arthur Sakamoto, Roger Wojtkiewicz, and three anonymous reviewers for advice and comments on earlier drafts of this paper; and to Bengt Muthén, both for making his LISCOMP software available and for providing help during the preparation of this article.*

SOCIOLOGICAL METHODS & RESEARCH, Vol. 17 No. 4, May 1989 325-352

have generally avoided discrete dependent variables or have transformed them into continuous variables when using structural equation models. There is a need for methods of analysis that are accessible and understandable as well as illustrative examples before sociologists will routinely apply structural equation models to analyze discrete dependent variables.

This article is intended to help serve this purpose. Unlike earlier works on discrete dependent variables in structural equations, this article introduces the subject through concrete sociological examples rather than through formal mathematics. The examples are drawn from a study of entry into scientific occupations. Extensions of these models to other research areas, however, should be straightforward. For didactic purposes, the following models are kept simple. The assumption of threshold measurement is shown to allow the linear relationships among observed and latent continuous variables to be treated in the same way as in conventional structural equation models in the LISREL framework. The models presented are simple cases of a large class of models that can be estimated with the computer program LISCOMP.

THE ANALYSIS OF OCCUPATIONAL DESTINATION IN THE STRATIFICATION LITERATURE

The recent history of the study of social stratification and mobility has witnessed the critical role of path analysis and structural equation models in bringing status-attainment research to the state of cumulative "normal science" (Bielby, 1981; Featherman, 1981). The classic Blau-Duncan model, the Wisconsin model, and extended versions of both have successfully illustrated how family background affects one's social status in modern society (Blau and Duncan, 1967; Sewell et al., 1969; Duncan et al., 1972; Sewell and Hauser, 1975; Hauser et al., 1983). The power of path analysis and structural equations in these models is not simply to ascertain the total effects of parental characteristics on their offspring's status attainment in terms of reduced form coefficients, but rather to partition the total effects into direct and indirect effects through intermediate processes in terms of structural coefficients. For example, education has been found to be a critical intervening factor that both transmits the influence of family background and introduces effects of its own (Blau and Duncan, 1967; Duncan et al., 1972). Over the last two decades, many other intervening variables have been hypothesized and tested in modeling the causal process of status attainment (for a review, see Campbell, 1983).

The traditional approach of structural equations in the LISREL framework is restricted to analyzing continuous dependent variables. This limitation stems from the fact that structural equations are systems of linear regression equations. When dependent variables are discrete rather than continuous, linear models are not appropriate (Hanushek and Jackson, 1977:180-186; Maddala, 1983:15-16). This limitation of traditional structural equation models has given rise to a renewed interest in the analysis of mobility tables, which lost its popularity for many years following Duncan's (1966) article, and to the methodological innovations in the form of loglinear models (Featherman and Hauser, 1978; Goodman, 1978, 1984; Duncan, 1979; Hauser, 1979; Sobel et al., 1985). The shift in interest is justified because for many research questions, such as those concerning occupational destination, occupation cannot be treated as a continuous variable through the common practice of transforming occupations into Duncan SEI scores. In these cases, occupation should be treated as a discrete variable. Unlike structural equation models, the loglinear analysis of mobility tables accounts for the discreteness of occupations. Moreover, the analysis of mobility tables allows us to investigate "channels" and "barriers" in the mobility process, to use Blau and Duncan's terminology (1967:117), which are not subject to study within the approach of structural equations using Duncan SEI scores (Yamaguchi, 1983).

Unfortunately, the loglinear analysis of mobility tables raises other problems. In theory, the discrete coding of occupations contains more information than any occupational scoring, because the latter can be obtained from the former but not vice versa. In practice, however, a too-detailed classification of occupations not only makes modeling unfeasible, but more importantly, it also hinders a meaningful interpretation of the results. As a consequence, researchers collapse detailed occupational codes into major categories that are relatively homogeneous; but the cost of collapsing occupational categories is the loss of information. Even though the use of Goodman's (1981) statistical tools minimizes information loss, it requires a strong conviction to believe that occupations within a major occupational category are so homogeneous that they can be treated as if they were identical.

Another shortcoming of the loglinear analysis of mobility tables is the tendency to neglect intervening factors by devoting full attention to two-way, origin-destination tables. Although path-analysis-like loglinear models are possible for analyzing categorical data (e.g., Goodman, 1973), they are rarely used in empirical research. Limitations of causal analysis involving loglinear models are widely known (Fienberg, 1980:120-134). These limitations derive in part from the fact that, no matter how the researcher envisions a causal relationship, the assumptions underlying loglinear analysis are such that all variables are treated in a symmetrical way in the process of estimation (Bishop et al., 1975). The classical distinction between independent, or exogenous, variables and dependent, or endogenous, variables is blurred. From here, the econometricians Heckman (1978) and Manski and McFadden (1981) launch their critiques of the pervasive use of loglinear models. To them, the loglinear analysis of discrete data is analogous to the correlation analysis of continuous data and therefore is incapable of uncovering structural relationships.

The models presented in this article are constructed to fill the gap between the structural equations approach on the one hand and the loglinear analysis approach on the other. The models treat observed ordinal variables as outcomes of latent continuous variables that cross fixed thresholds while retaining the structural components of conventional structural equations. This is achieved with additional assumptions. Consequently, certain limitations of this approach are noted below.

STRUCTURAL EQUATION MODELS WITH ORDINAL DEPENDENT VARIABLES: LISCOMP MODELS

Historically, the problem of discrete variables arose in correlation analysis. For a pair of dichotomous variables, the value of the Pearson product moment correlation between them depends not only on the strength of the relationship but also on the means of the variables (for reviews, see Fienberg, 1980; Winship and Mare, 1983; Mislevy, 1986). The analytical results of Olsson (1979) and the Monte Carlo results of Muthén and Kaplan (1985) provide direct evidence that using consecutive values (e.g., 0, 1, 2, 3) to code ordinal variables (when the variables are outcomes of crossing thresholds on latent continuous variables distributed as multivariate normal) leads to incorrect statistical inferences in factor analysis. The review of Bentler and Chou (1987), however, suggests that when a variable has more than four categories, the ordinary methods may not be worse than other alternatives. When there are only three or fewer categories, the researcher should consider other procedures that account for the discreteness of the variable.

Constructing other types of correlation coefficients is one solution to this problem. Jöreskog and Sörbom (1986) have programmed routines to compute canonical correlations, normal score correlatons, polychoric correlations, and polyserial correlations in their program PRELIS, which is used in combination with LISREL VII (Jöreskog and Sörbom, 1987). In brief, a canonical correlation is the correlation between two ordinal variables whose values are replaced by optimal scores that maximize the correlation; a normal score correlation is that between two ordinal variables whose values are replaced by normal scores determined from their marginal distributions; a polychoric correlation is one between two latent continuous variables that are assumed to be distributed as bivariate normal and to have generated the observed ordinal variables through thresholds; and a polyserial correlation is that between an observed continuous variable and a latent continuous variable that underlies an ordinal variable, assuming that the observed and the latent continuous variables follow a bivariate normal distribution. See Kendall and Stuart (1979, chapters 26 and

33) and Jöreskog and Sörbom (1986, chapter 1) for explanations of these types of correlations.

Jöreskog and Sörbom (1984, 1987) recommend replacing Pearson product moment correlations with polychoric and polyserial correlations. This solution assumes bivariate normality between two latent continuous variables (in the case of polychoric correlations) or between an observed and a latent continuous variable (in the case of polyserial correlations). Psychologists are generally comfortable with using polychoric and polyserial correlations because they can assume in factor analysis that latent factors are normally distributed. For structural analysts in sociological and economic research, however, polychoric and polyserial correlations are not very helpful because they would violate the desirable property of parameter invariance with respect to changes in the marginal distributions of the independent variables. This invariance property requires that assumptions be made about error terms rather than about variables themselves.

Instead, sociologists and economists have approached the problem from another direction: probit regressions (Heckman, 1978; Winship and Mare, 1983).[1] In a standard probit regression, a latent continuous variable is hypothesized to underlie an observed ordinal variable (including a dichotomous variable as a special case). The observed ordinal variable is the indicator of the latent continuous variable through crossing thresholds. The latent variable is assumed to be linearly dependent upon predetermined variables, and the error term is assumed to be distributed as standard normal. The idea behind the incorporation of probit regressions into structural equation models is simple: replace ordinal variables with their latent counterparts when the ordinal variables are dependent variables. When ordinal variables are independent, the researcher has the choice of using numerical codings, dummies, or their latent counterparts (Heckman, 1978; Winship and Mare, 1983, 1984).

This article assumes that both independent and dependent ordinal variables enter a structural equation model in the form of latent variables. With this restriction, a unified framework can be reached in which ordinal variables are incorporated into structural models while the structural part of conventional structural equations remains intact. This case can be handled within Muthén's LISCOMP program

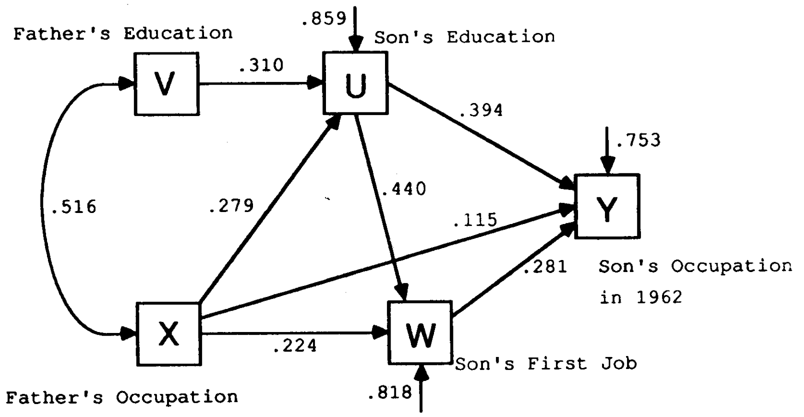

Figure 1: Blau-Duncan Model

Source: P. 170, *The American Occupational Structure* by Peter M. Blau and Otis Dudley Duncan. Copyright 1967 by Peter M. Blau and Otis Dudley Duncan. Reproduced by permission of The Free Press, a Division of Macmillan, Inc.

(Muthén, 1983, 1984, 1987). From this point on, these types of models are referred to as "LISCOMP models."

The restriction that ordinal variables enter structural equations only indirectly through their latent variables is needed so that general models can be estimated. Although other programs (Winship and Mare, 1983; Avery and Hotz, 1985) can estimate simple models without this restriction, more general models are hindered by computational difficulties. By adding this restriction, all models currently estimated with LISREL for continuous variables can be estimated with LISCOMP for ordinal variables. These include nonrecursive models (Duncan, 1975), MIMIC models (Hauser and Goldberger, 1971), exploratory and confirmatory factor analysis (Long, 1983), multiple-indicator models (Bielby et al., 1977), and models decomposing contextual and individual effects (Hauser, 1988). Like LISREL, LISCOMP is also capable of estimating models that compare independent samples from multiple populations. Moreover, Tobit models for censored dependent variables (Maddala, 1983; Amemiya, 1985; Mare and Chen, 1986) can be incorporated into structural equation models within the unified framework. In this article, simple examples are presented to illustrate the potential usefulness of LISCOMP models. For a description of the full features of LISCOMP, consult the LISCOMP manual (Muthén, 1987) and other papers (Muthén, 1983, 1984).

Although they are restrictive in the way in which ordinal variables enter structural equations as independent variables, the LISCOMP models are potentially very useful in sociological research. The remainder of this article is devoted to illustrating how these models are applied to analyze the problem of occupational destination.

MODELS OF OCCUPATIONAL DESTINATION: WHO BECOME SCIENTISTS AND ENGINEERS?

The data are from the 1962 Occupational Changes in a Generation (OCG) Survey. A large, nationally representative sample of the United States male population, the OCG survey was conducted by the Bureau of the Census as a supplement to the 1962 March Current Population Survey (CPS) (Blau and Duncan, 1967). Historically, the OCG survey and the subsequent Blau-Duncan model have served as the cornerstones for later studies of social stratification. Figure 1 summarizes Blau and Duncan's (1967) basic findings about the way in which a father's characteristics affect a son's social status. The numbers on the diagram are path coefficients. The son's occupation (Y) and first job (W) and the father's occupation (X) are measured in Duncan SEI scores. Blau and Duncan found that most of the influence of the father's status (V, X) on the son's occupation (Y) is mediated by the son's education (U) and first job (W). In particular, they specified that there is no direct effect of the father's education (V) on the son's first job (W) and current occupation (Y). In the language of structural equations, the paths from V to W and from V to Y are constrained to be zero.

In the present analysis, our first consideration is how family background affects one's occupational destination as a scientist or engineer. A study of one's destination as a scientist or engineer not only

TABLE 1
Correlation Matrix and Sample Statistics of the Exogenous Variables

Variable	V	X
V: Father's Education	1.000	
X: Father's Occupation (SEI)	.467	1.000
Mean	7.64	27.40
Standard Deviation	4.00	21.16

SOURCE: 1962 OCG Survey. The sample size is 14,401. See text for definitions of variables.

sheds light on the long-standing question of how scientists and engineers are different from the general public in their social origins (for a review, see Rever, 1973), but also contributes to our understanding of social stratification in general (Xie, 1988). This is so because scientists and engineers constitute a group that enjoys considerable prestige, which generally ranks near the top (Duncan, 1961; Hodge et al., 1964; Stevens and Featherman, 1981). There is reason to suspect, however, that scientists and engineers differ from other social "elites" such as politicians and businessmen. Scientific and engineering jobs almost always require much education and formal training. The overwhelming majority of scientists and engineers have bachelor's degrees. It is then reasonable to hypothesize that parental characteristics affect one's likelihood of becoming a scientist or engineer almost entirely through education. That is, conditioned on educational attainment, parental characteristics do not affect one's likelihood of being a scientist or engineer. In contrast, entry into a business career may be mediated by education to a much smaller degree. Past research has partially supported this hypothesis. Parental status has been found to have a very small effect on the offspring's transition to further education (Mare, 1980) and occupational placement (Hout, 1988) among college graduates. Therefore, some departure from the Blau-Duncan model is expected in that the father's occupation affects the son's destination as a scientist or engineer only indirectly through education.

For this analysis, all 25-64-year-old males for whom CPS and OCG files were successfully merged are included. Observations are ex-

TABLE 2
Descriptive Statistics of Discrete Dependent Variables

Variable	Code	Meaning	Percent
S: Current Occupation	0	Non-scientific/engineering	96.4
	1	Scientific/engineering	3.6
F: First Job	0	Non-scientific/engineering	98.3
	1	Scientific/engineering	1.7
E: Education	0	0-7 years	13.4
	1	8-11 years	32.6
	2	12 years	29.0
	3	13 and more years	25.0

SOURCE: 1962 OCG Survey. The sample size is 14,401. See text for definitions of variables.

cluded with nonresponse or invalid response to any of the following five survey questions: respondent's 1962 occupation, respondent's first full-time job after school, respondent's education, father's education, and father's occupation. This leaves 14,401 observations.

To measure who are scientists and engineers, a variable S is created that equals 1 for scientists and engineers but 0 otherwise. Variable S is constructed from the 1960 detailed census occupational codes. We code S equal to 1 for those whose reported occupations fall into a set of occupational categories that the Bureau of the Census defines as constituting the scientific and engineering professions (U.S. Bureau of the Census, 1969).[2] By the same rule, a dichotomous variable F is made for the first job after completing school. Variable F equals 1 if the first job is in science and engineering but 0 otherwise. The means of S and F are 0.036 and 0.017, respectively. The son's education was collapsed from the original nine categories to four categories (0-7, 8-11, 12, and 13+).[3] The same categorization is adopted by Winship and Mare (1984) in their exposition of ordered probit regression using the same data. The ordinal variable that measures the son's education is denoted as E to distinguish it from the continuous variable U. Variable V is measured by the midpoints of intervals of years of father's schooling; variable X is father's SEI score. For descriptive statistics of variables V, X, S, F, and E, see Tables 1 and 2.

THE MEASUREMENT MODELS

In Jöreskog and Sörbom's LISREL framework, measurement models have played an important role in the development of structural equation models. They have brought several statistical tools (e.g., path analysis, structural equations, factor analysis, and reliability analysis) together into a unified approach (Jöreskog and Sörbom, 1984, 1987). In this framework, all of the structural relationships, causal or noncausal, are between latent factors. These latent factors manifest themselves through observed variables. The relationships between latent factors and observed variables form "measurement models." For the special case of classical path models without latent constructs, latent factors are simply allowed to be identical to observed variables.

When all dependent variables are continuous, measurement models are traditionally constructed by specifying a set of linear regression equations regressing observed variables on latent factors. One major use of these measurement models is to set constraints on the observed variables, thus allowing for hypothesis testing and assessment of measurement errors (for example, Hauser and Goldberger, 1971; Bielby et al., 1977; Hauser et al., 1983). When observed dependent variables are ordinal, however, another type of measurement model is needed to link observed ordinal variables to unobserved continuous variables in a nonlinear and nonstochastic way through thresholds.[4] Measurement models become critical in an analysis of ordinal dependent variables.

In a measurement model of thresholds, there is a one-to-one correspondence between an ordinal variable and its latent counterpart. To denote the unobserved variable, a star is placed next to the name of its corresponding observed variable. For example, assume that there is an unobserved continuous variable S^* that underlies the observed dichotomous variable S. The variable S^* can be thought of as measuring one's latent tendency of becoming a scientist or engineer. More formally, specify:

$$\begin{aligned} S_i &= 1 \quad \text{if } S_i^* > 0 \\ S_i &= 0 \quad \text{otherwise} \end{aligned} \qquad [1]$$

Latent	$E^* \leq \alpha_1$	$\alpha_1 < E^* \leq \alpha_2$	$\alpha_2 < E^* \leq \alpha_3$	$\alpha_3 < E^*$
Observed	E = 0	E = 1	E = 2	E = 3

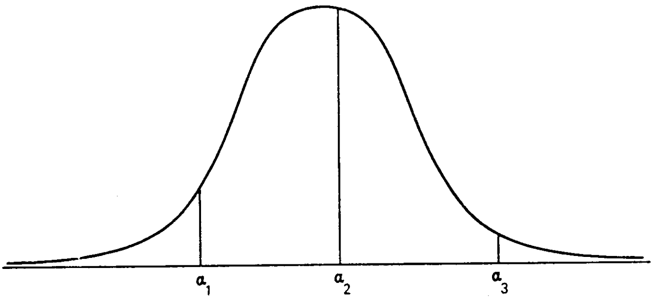

Figure 2: A Graphic Presentation of the Measurement Model for Variable E

where the subscript i stands for the ith observation. Equation (1) says that if everyone has a continuous, latent tendency to go into scientific or engineering work, then some become scientists or engineers if their latent tendencies exceed a threshold. Here the choice of 0 as the threshold is arbitrary, because in practice the intercept term of the regressors will absorb any fixed value. Similarly, we have a measurement model relating F and F*:

$$F_i = 1 \quad \text{if } F_i^* > 0 \qquad [2]$$
$$F_i = 0 \quad \text{otherwise}$$

The above measurement model can be extended to the ordered response case for variable E. Because variable E has four categories, a measurement model with three thresholds is needed:

$$E_i = 3 \quad \text{if } \alpha_3 < E_i^* \qquad [3]$$
$$E_i = 2 \quad \text{if } \alpha_2 < E_i^* \leq \alpha_3$$
$$E_i = 1 \quad \text{if } \alpha_1 < E_i^* \leq \alpha_2$$
$$E_i = 0 \quad \text{if } E_i^* \leq \alpha_1$$

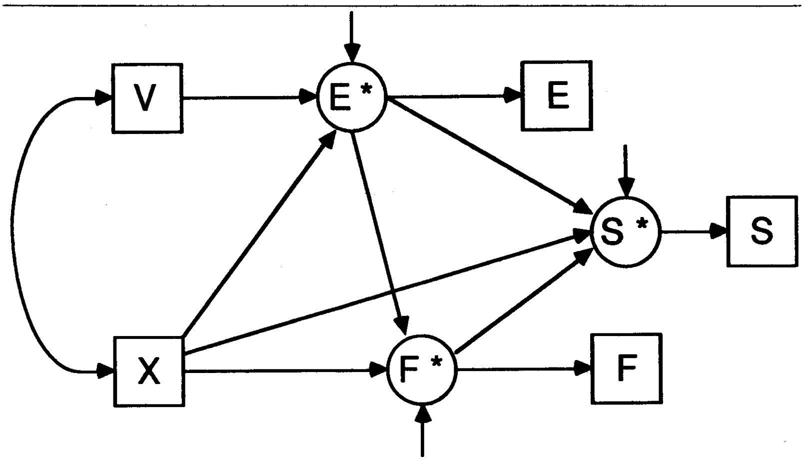

Figure 3: Structural Modeling of the Occupational Destination of Scientist or Engineer, Model 1

where the α's are the threshold parameters defining categorical intervals on E^*. For a sample of a single group, the estimation of the α's themselves is not interesting because they are completely determined by the marginal distribution of E after the distributional form of E^* is assumed in normalization (this is discussed in more detail later).[5] These estimates are not reported.

Figure 2 graphically illustrates the measurement model for the E variable. It is shown that the observed ordered categorical variable E is assumed to be a discrete translation of a latent continuous variable E^*. There are three thresholds (α's) that divide the whole distribution of E^* into four intervals. The E variable takes discrete jumps when E^* crosses the thresholds.

Clearly, this type of measurement model is different from traditional measurement models in the LISREL framework. Muthén (1983) has named it "outer" measurement in contrast to the traditional "inner" measurement. To emphasize the distinction between the two types of measurement models, S^*, F^*, and E^* are called "latent variables" or "unobserved variables," and the terms "latent factors" and "theoretical constructs" are reserved for traditional "inner" measurement models. For models with multiple indicators that are ordered polytomous or dichotomous, it is necessary to combine both types of measurement models, "inner" and "outer." In this way, the structural part of conventional structural equation models remains the same. In the course of developing LISCOMP, Muthén has incorporated these two types of measurement models into linear structural equation analysis. This is where the term "LISCOMP" comes from, an acronym for the "Analysis of *Li*near *S*tructural Relations Using a *Comp*rehensive Measurement Model."

THE STRUCTURAL MODELS

Our first model, which is shown in Figure 3, is based on the Blau-Duncan model. Squares indicate observed variables, and circles indicate latent variables. The diagram shows the one-to-one correspondences between the observed variables S, F, and E, and the latent variables S^*, F^*, and E^*. These form the measurement models. For the structural part, the following regression equations are used:

$$S^* = \beta_{S^*1}1 + \beta_{S^*F^*}F^* + \beta_{S^*E^*}E^* + \beta_{S^*X}X + \varepsilon_{S^*} \quad [4]$$
$$F^* = \beta_{F^*1}1 + \beta_{F^*E^*}E^* + \beta_{F^*X}X + \varepsilon_{F^*}$$
$$E^* = \beta_{E^*1}1 + \beta_{E^*V}V + \beta_{E^*X}X + \varepsilon_{E^*}$$

where the β's are regression coefficients with the first subscript denoting the dependent variable and the second subscript denoting the regressor; the 1's are intercept terms, and the ε's are error terms. The ε's are assumed to be independent and identically distributed (i.i.d.) as standard normal with the cumulative probability function being

$$F(z) = \int_{-\infty}^{z} \frac{1}{(2\pi)^{1/2}} exp[-(t^2/2)]dt$$

The equations then are separate probit regressions (Hanushek and Jackson, 1977:179-216; Maddala, 1983:13-57; Amemiya, 1985:268-286). The S^* and F^* equations are ordinary binary probit regressions, and the E^* equation is an ordered probit regression (Winship and Mare, 1984).

The variances of ε's need to be normalized or the variances of latent variables S^*, F^*, and E^* will be indeterminate. For "inner"measurement models in conventional structural equations, normalization can take one of two forms. The variance of a latent factor can be standardized (usually to 1) or the variance of the error term when the latent factor is a dependent variable can be standardized. Or, one of its loadings can be set to a constant (usually to 1). In the case of "outer" measurement models with observed ordinal variables, loadings are nonlinear and nonstochastically defined in equations (1)-(3). *In addition*, the variances of the latent variables need to be normalized because "outer" measurement models do not define the scales of the latent variables. We can normalize either the variances of the latent variables or the variances of the errors. Within the syntax of LISCOMP, each of the error variances can be conveniently set to 1. Even though logit models are widely used in the analysis of discrete data, and the choice of the probit versus the logit model is usually inconsequential for a single equation model with data from random sampling (e.g., Maddala, 1983:23), it is necessary to use the probit in structural equation models in order to account for a possible error covariance structure (Winship and Mare, 1983:103-104).

A distinctive feature of the model here is that neither the exogenous variables (X and V) nor the latent variables (S^*, F^*, and E^*) are assumed to be normal. Rather, our normality assumption pertains to the error terms (ε_{S^*}, ε_{F^*}, and ε_{E^*}). The exogenous variables (X and V) are unrestricted and retain their original observed values. This contrasts with the practice of using polyserial correlations, which assume bivariate normality for the pair of a latent and an observed continuous variable. In this model, the latent variables are distributed as multivariate normal *conditional* on the exogenous variables. Note that the sample statistics of the exogenous variables in Table 1 will not enter the estimation of the model. Rather, the estimation procedure is "conditional" on these statistics. In this model, the error covariances are specified to be 0. More complicated models may contain correlated errors.

ESTIMATION

In the present analysis, only one observed variable is available for each theoretical construct. The "inner" measurement model assumes

TABLE 3
Comparing the Fit of Three Models of the Occupational Destination of Scientist or Engineer

Model	Description	chi-square	DF
1	Blau-Duncan Model (Figure 3)	1.911	2
2	Deleting path from X to S^*	1.945	3
3	Deleting paths from X to S^* and F^*	2.042	4

NOTE: The sample size is 14,401. Chi-square stands for the large sample chi-square statistic as reported in LISCOMP output. DF is the degrees of freedom associated with the chi-square statistic.

that the theoretical constructs are identical to their indicators, or that there are no measurement errors. With the "outer" measurement models (1)-(3), the dichotomous and ordered polytomous dependent variables S, F, and E can be incorporated into the general framework of structural equations as shown in (4). There, only latent variables and exogenous variables are used. The observed ordinal variables are left out of the structural equations. An unobserved/observed pair can be conveniently treated as a single variable.

Full information likelihood estimation is unfeasible at the present time for most models of this kind because of computational difficulties of integration over the multivariate normal distribution. Instead, Muthén's LISCOMP provides a three-stage limited information generalized least squares (GLS) estimator. Muthén's GLS gives consistent estimates of parameters and their standard errors, and provides a large-sample chi-square test of model fit. Moreover, the difference in chi-squares between two nested models follows a chi-square distribution with degrees of freedom equal to the difference in the degrees of freedom of the two models, given that the more restrictive model is correct. Muthén's GLS solution is fast enough for practical use with a reasonable number of latent variables (fewer than 20) (Muthén, 1983; Mislevy, 1986). Because the GLS estimates are only asymptotically correct, large samples are required for the estimates to be trustworthy. In the following, Muthén's GLS is used directly without explanation of the estimation procedures. Readers interested in Muthén's GLS should consult other materials (Muthén, 1983; Muthén, 1984).

TABLE 4
Estimated Structural Probit Coefficients for Model 1, Table 3

Dependent Variable	Independent Variables F^*	E^*	X	V	R^2
E^*			0.018 (0.001) [0.321]	0.092 (0.003) [0.310]	0.291
F^*		0.607 (0.020) [0.585]	0.000 (0.001) [0.000]		0.342
S^*	0.461 (0.025) [0.449]	0.246 (0.023) [0.231]	0.000 (0.001) [0.000]		0.376

NOTE: Standard errors are in parentheses. Path coefficients are in brackets. For definitions of variables, see text and Figure 3. Estimates were obtained using LISCOMP. For model fit, see Table 3.

RESULTS

The measurement of goodness of fit for Model 1 is reported in the first line of Table 3. Estimates of the structural coefficients, their standard errors, and path coefficients are given in Table 4.[6]

Variables V and X have natural scales, given in Table 1, but the scales of latent variables S^*, F^*, and E^* are not defined until the error variances are set to 1's. The variances of S^*, F^*, and E^* are determined by the estimated coefficients and variances of the predetermined variables. For example,

$$V(E^*) = \beta^2_{E^*V}V(V) + \beta^2_{E^*X}V(X) + 2\beta_{E^*V}\,\beta_{E^*X}\,Cov(V,X) + V(\varepsilon_{E^*}) \quad [5]$$

where we know that $V(\varepsilon_{E^*})$ is normalized to 1. From this procedure, calculation gives: $V(E^*) = 1.41$, $V(F^*) = 1.52$, and $V(S^*) = 1.60$.

Once the estimated variances of the latent variables are known, R^2's and path coefficients can be easily calculated.[7] Note that both the variances of the latent variables and the R^2's, unlike the usual case with continuous dependent variables, are not sample analogs of population moments because these sample analogs do not exist for probit regressions. Instead, the reported numbers are estimates that are only asymptotically correct (McKelvey and Zavoina, 1975:112).

TABLE 5
Estimated Structural Probit Coefficients for Model 3, Table 3

Dependent Variable	Independent Variables F^*	E^*	X	V	R^2
E^*			0.018 (0.000) [0.321]	0.092 (0.003) [0.310]	0.291
F^*		0.603 (0.018) [0.582]			0.339
S^*	0.463 (0.024) [0.450]	0.246 (0.022) [0.231]			0.377

NOTE: Standard errors are in parentheses. Path coefficients are in brackets. For definitions of variables, see text and Figure 4. Estimates were obtained using LISCOMP. For model fit, see Table 3.

Overall, Model 1 fits the data well (χ^2 = 1.911 for 2 degrees of freedom). A look at the estimates, however, reveals that the direct effects of a father's occupation on a son's likelihood of being a scientist or engineer for first and current jobs are estimated to be 0. This finding supports the hypothesis that recruitment into scientific and engineering professions is mostly mediated by educational attainment. Family background has its effects, but only through making education more accessible. Controlling for education, the chances of being a scientist or engineer are virtually the same for everyone. To test this hypothesis formally in a different way, further restrictions are made in Models 2 and 3, as shown in Table 3. Observe that deleting the paths from X to F^* and E^* does not increase the χ^2 measure by much. Taking the difference in the χ^2 statistics between the two nested models (Models 1 and 3), we have a χ^2 test statistic of 0.131 for two degrees of freedom. The parsimonious model, Model 3, is therefore retained. The hypothesis that the effect of parental characteristics on the entry into scientific and engineering occupations is mediated by education is confirmed. Table 5 displays the estimated parameters for Model 3. For a graphic presentation of the final model, see Figure 4.

The parameter estimates are probit coefficients, interpretations of which can be made in terms of probabilities through nonlinear transformations. Because the latent variables do not have natural scales, it

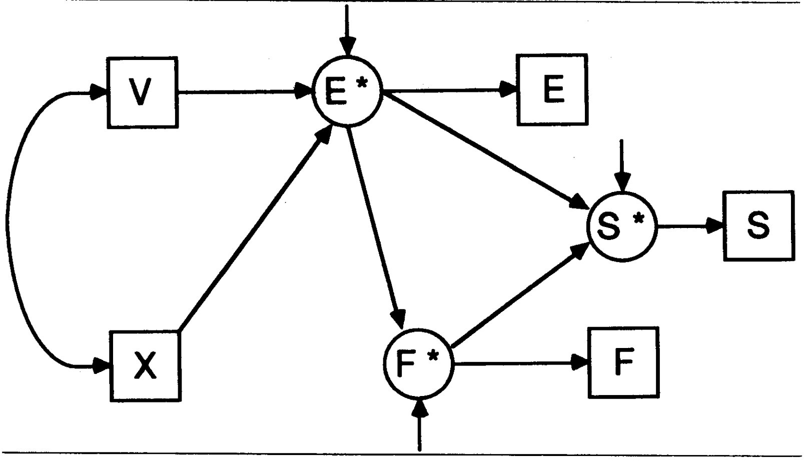

Figure 4: Structural Modeling of the Occupational Destination of Scientist or Engineer, Model 3

is probable that, unlike the usual case with continuous dependent variables, the path coefficients, which presume unit variances of the latent and observed variables, are more meaningful than the regression coefficients.

To interpret these effects in terms of probabilities, evaluation can be done at the sample means of the dependent variables. For example, to determine the effect of education on the likelihood of being a scientist or engineer, evaluation is done at the mean of S (0.036, Table 2). Let $\alpha_{S^*E^*}$ be the effect of E^* on S^* in the metric of path coefficients. The effect in probability ($\rho_{S^*E^*}$) can be written as:[8]

$$\rho_{S^*E^*} = \alpha_{S^*E^*} \times \sigma_{S^*} \times \phi(\Phi^{-1}(M_S)) \qquad [6]$$

where σ_{S^*} is the standard deviation of the latent variable S^*, ϕ is the standard normal density function, Φ^{-1} is the inverse function of the standard normal cumulative function, and M_S is the sample mean of S. The formula is derived from Hanushek and Jackson (1977:189). The standard deviation of S^* is needed to convert the scale of the path coefficient ($\alpha_{S^*E^*}$) into that of a probit coefficient. That is, $\alpha_{S^*E^*} \times \sigma_{S^*}$ gives the standardized probit coefficient, or the induced change in the probit as a result of a standard deviation change in the independent variable. If the researcher prefers to evaluate the effect in probability in terms of the original scale of the independent variable, he or she can substitute the structural probit coefficient ($\beta_{S^*E^*}$) for $\alpha_{S^*E^*} \times \sigma_{S^*}$ in (6).

Equation (6) states that the effect of the independent variable E^* on the probability that $S = 1$ is nonlinear, depending on the sample mean of S, where the effect in probability is evaluated. The effect reaches the maximum at $M_S = 0.5$ and decreases symmetrically toward 0 as M_S moves to both extremes (0 and 1). Therefore, the $\rho_{S^*E^*}$ coefficient cannot be a structural parameter, because a change in the marginal distribution of other variables will affect M_S and consequently will affect the $\rho_{S^*E^*}$ coefficient.

One can interpret a ρ coefficient as the relative change in dependent probability induced by a standard deviation change in the predetermined variable. From equation (6), a standard deviation change in E^* can be calculated to introduce a change of 0.0292 in the probability of $S = 1$. Compared to the sample mean of S (0.036), this is not a small number.

The rule for decomposing total effects into direct and indirect effects in conventional structural equation models (Duncan, 1975) still holds for LISCOMP models. From Table 5, the total effect (in the metric of path coefficients) of V on S^* can be calculated to consist of two indirect effects: $V \rightarrow E^* \rightarrow S^*$ (0.072) and $V \rightarrow E^* \rightarrow F^* \rightarrow S^*$ (0.083). Likewise, the total effect of X on S^* can be decomposed into indirect effect $X \rightarrow E^* \rightarrow S^*$ (0.074) and indirect effect $X \rightarrow E^* \rightarrow F^* \rightarrow S^*$ (0.084). The direct effects of V and X on F^* and S^* have been specified to be 0 in the model. The total effect of V on S^* is 0.153, and that of X on S^* is 0.158. They are of a similar scale. Compare the results with the original Blau-Duncan model, which is concerned with the general process of status attainment. It can be easily calculated from Figure 1 that the total effect of V on Y is 0.160, which is very close to the estimate of the total effect of V on S^* (0.153). But the total effect of X on Y is 0.322, a number much larger than that of X on S^* (0.158) in the model. In terms of probability, we can follow the same procedure as equation (6) and obtain that the total effect of V on S in probability is 0.0193, and that of X is 0.0199.

To summarize, it is shown that scientific and engineering occupations have a recruitment pattern that is different from the Blau-Duncan status attainment model. A father's occupation affects a son's likelihood of being a scientist or engineer by affecting the son's educational attainment. Beyond that, a father's status (either his occupation or his education) does not have an effect. Or, in the terminology of structural modeling, the direct effects of a father's education (V) and occupation (X) on a son's status of being a scientist or engineer (S) have been found to be 0.

ANOTHER EXAMPLE: WHO BECOME MANAGERS, OFFICIALS, AND PROPRIETORS?

Are scientists and engineers truly unique? Or is the structural equation model with occupational destination as the dependent variable incapable of detecting the direct effect of family background? In this section of the article, another occupational group—managers, officials, and proprietors—is studied.

Managers, officials, and proprietors are defined according to the 1960 census occupational codes. Farmers are excluded.[9] As do scientists and engineers, the group of managers, officials, and proprietors generally have high social status (Duncan, 1961; Blau and Duncan, 1967; Stevens and Featherman, 1981). The recruitment process into these occupations, however, should not be much different from the general pattern of vertical mobility observed by Blau and Duncan. This should be true because high status families have economic resources and social networks that can directly assist their offspring toward successful careers as managers, officials, or proprietors. This direct effect is not completely mediated by education (Yamaguchi, 1983). Given the same education, a child from a low status family faces more barriers to success. Because there are many important factors that are not related to formal education, he cannot overcome all of his disadvantages through education. Therefore, it is not unreasonable to assume that parental characteristics have a direct effect on one's likelihood of becoming a manager, official, or proprietor.

The procedure for testing this hypothesis is similar to the previous one. We define a dichotomous variable B, which equals 1 if the respondent is in the occupations of managers, officials, and pro-

TABLE 6
Comparing the Fit of Three Models of the Occupational Destination of Manager, Official, or Proprietor

Model	Description	chi-square	DF
1	Blau-Duncan Model	3.545	2
2	Deleting path from X to B^*	27.595	3
3	Deleting paths from X to B^* and T^*	95.441	4

NOTE: The sample size is 14,401. Chi-square stands for the large sample chi-square statistic as reported in LISCOMP output. DF is the degrees of freedom associated with the chi-square statistic.

prietors, but equals 0 otherwise. Similarly, T equals 1 if his first job is in these occupations but 0 otherwise. B and T have means of 0.157 and 0.018, respectively. Corresponding to B and T, latent variables B^* and T^* are constructed. The four-category coding of son's education E and its latent counterpart E^* is retained. Father's education V and father's occupational SEI score X remain unchanged. The three models that were run before are estimated with these different dependent variables. The test statistics of model fit are reported in Table 6.

It is evident from Table 6 that the Blau-Duncan model holds well for modeling the process of becoming managers, officials, and proprietors. A father's occupational status directly affects a son's likelihood of becoming a manager, official, or proprietor at his first job and current job. The effect of family background is not completely mediated through son's education. The χ^2 tests between Model 1 and Model 2 (24.050 for 1 degree of freedom) and between Model 1 and Model 3 (91.896 for 2 degrees of freedom) reject the parsimonious Model 2 and Model 3 in favor of Model 1. In Table 7, all of the estimated coefficients are positive and significantly different from 0. The hypothesis is verified that offspring from high status families are more likely to become managers, officials, and proprietors given the same amount of education. This result reconfirms Yamaguchi's (1983) finding that education explains the effect of fathers' occupations on the likelihood of being professionals, but not the likelihood of being managers, officials, or proprietors. Notice also that the path coefficients of E^* on T^* and B^* are smaller than those of E^* on F^* and S^* in Table 5. This suggests that education is a less powerful determinant of the recruitment process into managers, officials, and proprietors than that into science and engineering. As a consequence, the R2's of

TABLE 7
Estimated Structural Probit Coefficients of Model 1, Table 6

Dependent Variable	Independent Variables T*	E*	X	V	R^2
E*			0.018 (0.001) [0.321]	0.092 (0.003) [0.310]	0.291
T*		0.213 (0.026) [0.240]	0.006 (0.001) [0.121]		0.099
B*	0.320 (0.030) [0.315]	0.101 (0.016) [0.112]	0.004 (0.001) [0.079]		0.128

NOTE: Standard errors are in parentheses. Path coefficients are in brackets. For definitions of variables, see text. Estimates were obtained using LISCOMP. For model fit, see Table 6.

T* and *B* * equations are smaller than those of *F* * and *S* * equations in Table 5.

CONCLUSION

This analysis of the process of becoming scientists and engineers and the process of becoming managers, officials, and proprietors has demonstrated how one can study occupational destination within the structural equations approach. It has been shown that different occupations may have different recruitment patterns, suggesting that the occupational structure is nonlinear and multidimensional. By focusing on entries into particular occupations, knowledge of how social mobility operates through various "channels" increases. Science and engineering, for example, were shown to be almost completely mediated by educational attainment. There, parental characteristics affect one's destination as a scientist or engineer only indirectly, by making education more accessible. In contrast, one's likelihood of becoming a manager, official, or proprietor is largely dependent on the father's social status, given the same amount of education.

The structural equations approach outlined in this paper has the advantage of modeling a causal structure with intermediate processes. Total effects are partitioned into direct and indirect effects in terms of structural coefficients. This is an important gain over loglinear analysis of mobility tables, which often focuses on two-way mobility tables. The structural models of occupational destination are also an advance over conventional structural equations in the LISREL framework. Ordered polytomous variables and dichotomous variables need not be transformed into continuous variables on an arbitrary basis. The conditional probability of discrete dependent variables in a set of structural equations can be studied.

There are certain weaknesses in the models presented. Only dichotomous and ordinal variables have been dealt with. The more general case of unordered polytomous dependent variables cannot be handled within this approach. They need to be analyzed with loglinear models or various logit and probit models (Bishop et al., 1975; Maddala, 1983; Long, 1987). In our application to the occupational destination problem, this limitation means that only one occupation at a time can be dealt with because occupations cannot be formed into an ordinal variable. In these examples this problem was avoided by considering two pairs of occupational destinations separately. This solution has a heuristic value. But the results from two analyses cannot be formally combined together because the categorical divisions of the dependent variables overlap. Another limitation of these models is the assumption that there is a latent continuous variable underlying an observed discrete variable through a threshold measurement model. The assumption of a threshold measurement model may not be appropriate in all cases.

Nevertheless, these structural equation models of occupational destination open up more research areas and offer alternative research methods. They provide an example of sociological applications of the LISCOMP models, which can be viewed as a natural extension of structural equation models and probit analysis. The limitations listed in the paragraph above also apply to probit analysis. As long as the researcher knows when a probit analysis is appropriate, the incorporation of probit analysis into structural equation models can expand the capacity for analyzing discrete data. With the recent sophistication of the computer program LISCOMP, more sociological applications of structural equations with ordered dependent variables should be seen in the near future.

APPENDIX: AN EXAMPLE OF CONTROL FILES IN LISCOMP

The following LISCOMP control file was used to estimate Model 1 of Table 3. The estimated coefficients are reported in Table 4.

```
TI      BLAU-DUNCAN MODEL: SCIENTISTS AND ENGINEERS
DA IY=3 IX=2 NO=14401 TR=OT VT=OT
TE 1 1 3
TT 1 1 3
CT .5 .5 2.5 4.5 5.5
MO MO=SE P2 P3 NE=3 LY=FI BE=FI GA=FI PS=FI
FR GA(3,1) GA(2,2) GA(1,2) GA(3,2)
FR BE(2,3) BE(1,3) BE(1,2)
VA 1. LY(1,1) LY(2,2) LY(3,3)
VA 1. PS(1,1) PS(2,2) PS(3,3)
OU WF ES SE ET
RA FO
(F1.0,2X,F1.0,4X,F1.0,4X,F3.0,F2.0,3X)
```

NOTES

1. Winship and Mare (1983) also discuss binary models with responses generated from binomial trials. These types of models are not discussed here for two reasons. First, these models are not identifiable without auxiliary information. Second, with slight modifications, these models can be viewed as being of the same class of models as those considered in this article.

2. Specifically, the 1960 census occupational codes 21, 31-53, 80-93, 130-145, and 172-175 are used to distinguish scientists and engineers from others.

3. Different coding schemes also were tried, such as the original nine categories and the two categories (college education versus other). The results are very similar.

4. Although there are no explicit stochastic terms in measurement models (1-3), the structural equations (4) contain stochastic errors (ε's). These stochastic errors (ε's) can be viewed as stemming both from the measurement models (1-3) and from the structural models (4). For identification purposes, stochastic terms from both sources are combined into ε's in equations (4).

5. These thresholds divide the latent variable's support into intervals whose probabilities map those given by the observed ordinal variable. For example, if the latent variable E^* is distributed as standard normal, $\alpha_1 = \Phi^{-1}[P(E = 0)]$, $\alpha_2 = \Phi^{-1}[P(E = 0) + P(E = 1)]$, and $\alpha_3 = \Phi^{-1}[P(E = 0) + P(E = 1) + P(E = 2)]$, where Φ^{-1} is the inverse function of the standard normal cumulative probability, and $P(E)$ is the marginal probability of variable E ($E = 0, 1, 2, 3$).

6. The LISCOMP control file for this model is given in the Appendix. Additional control and output files are available from the author upon request.

7. For models with exogenous variables, such as those estimated in this article, it is not possible to obtain the correct R^2's and path coefficients from standardized solutions reported

by LISCOMP 0.1. This is because the LISCOMP standardized solution refers to the case of unit variances of latent variables *conditional* on exogenous variables. The path coefficients that are normally defined assume unit variances of all variables unconditional on exogenous variables. It is possible, however, to calculate path coefficients and R^2 using the procedure described in equation (5).

8. This formula applies to continuous independent variables. When the independent variable of interest is dichotomous (say, $D = 0, 1$), the proper way is to take the difference of two predicted probabilities, one evaluated at $D = 0$ and the sample means of all other independent variables, and the other evaluated at $D = 1$ and the sample means of all other independent variables.

9. In terms of the 1960 census occupational codes, the definition includes codes 250 to 290.

REFERENCES

AMEMIYA, T. (1985) Advanced Econometrics. Cambridge, MA: Harvard Univ. Press.

AVERY, R. B. and V. J. HOTZ (1985) HotzTran (User's Manual). Old Greenwich, CT: CERA Economic Consultants.

BENTLER, P. M. and C. P. CHOU (1987) "Practical issues in structural modeling." Soc. Methods & Research 16: 78-117.

BIELBY, W. T. (1981) "Models of status attainment," pp. 3-26 in D. J. Treiman and R. V. Robinson (eds.) Research in Social Stratification and Mobility, Vol. 1. Greenwich, CT: JAI Press.

BIELBY, W. T., R. M. HAUSER, and D. L. FEATHERMAN (1977) "Response errors of black and nonblack males in models of the intergenerational transmission of socioeconomic status." Amer. J. of Sociology 82: 1242-1288.

BISHOP, Y.M.M., S. E. FIENBERG, and P. W. HOLLAND (1975) Discrete Multivariate Analysis: Theory and Practice. Cambridge, MA: MIT Press.

BLAU, P. M. and O. D. DUNCAN (1967) The American Occupational Structure. New York: Wiley & Sons.

CAMPBELL, R. T. (1983) "Status attainment research: end of the beginning or beginning of the end?" Sociology of Education 56: 47-62.

DUNCAN, O. D. (1961) "A socioeconomic index for all occupations," pp. 109-138 in A. J. Reiss, Jr. (ed.) Occupations and Social Status. New York: Free Press.

DUNCAN, O. D. (1966) "Methodological issues in the analysis of social mobility," pp. 51-97 in N. J. Smelser and S. M. Lipset (eds.) Social Structure and Mobility in Economic Development. Chicago: Aldine.

DUNCAN, O. D. (1975) Introduction to Structural Equation Models. New York: Academic Press.

DUNCAN, O. D. (1979) "How destination depends on origin in the occupational mobility table." Amer. J. of Sociology 84: 793-803.

DUNCAN, O. D., D. L. FEATHERMAN, and B. DUNCAN (1972) Socioeconomic Background and Achievement. New York: Academic Press.

FEATHERMAN, D. L. (1981) "Stratification and social mobility: two decades of cumulative social science," pp. 79-100 in J. F. Short, Jr. (ed.) The State of Sociology: Problems and Prospects. Beverly Hills, CA: Sage.

FEATHERMAN, D. L. and R. M. HAUSER (1978) Opportunity and Change. New York: Academic Press.

FIENBERG, S. E. (1980) The Analysis of Cross-Classified Categorical Data, 2d ed. Cambridge, MA: MIT Press.

GOODMAN, L. A. (1973) "Causal analysis of data from panel studies and other kinds of surveys." Amer. J. of Sociology 78: 1135-1191.

GOODMAN, L. A. (1978) Analyzing Qualitative/Categorical Data: Log-Linear Models and Latent-Structure Analysis. Cambridge, MA: Abt Books.

GOODMAN, L. A. (1981) "Criteria for determining whether certain categories in a cross-classification table should be combined, with special reference to occupational categories in an occupational mobility table." Amer. J. of Sociology 87: 612-650.

GOODMAN, L. A. (1984) The Analysis of Cross-Classified Data Having Ordered Categories. Cambridge, MA: Harvard Univ. Press.

HANUSHEK, E. A. and J. E. JACKSON (1977) Statistical Methods for Social Sciences. New York: Academic Press.

HAUSER, R. M. (1979) "Some exploratory methods for modeling mobility tables and other cross-classified data," pp. 413-458 in K. F. Schuessler (ed.) Sociological Methodology 1980. San Francisco: Jossey-Bass.

HAUSER, R. M. (1988) "A note on two models of sibling resemblance." Amer. J. of Sociology 93: 1401-1423.

HAUSER, R. M. and A. S. GOLDBERGER (1971) "The treatment of unobservable variables in path analysis," pp. 81-117 in H. L. Costner (ed.) Sociological Methodology 1971. San Francisco: Jossey-Bass.

HAUSER, R. M., S.-L. TSAI, and W. H. SEWELL (1983) "A model of stratification with response error in social and psychological variables." Sociology of Education 56: 20-46.

HECKMAN, J. J. (1978) "Dummy endogenous variables in a simultaneous equation system." Econometrica 46: 931-959.

HODGE, R. W., P. SIEGEL, and P. ROSSI (1964) "Occupational prestige in the United States, 1925-63." Amer. J. of Sociology 70: 286-302.

HOUT, M. (1988) "More universalism, less structural mobility: the American occupational structure in the 1980s." Amer. J. of Sociology 93: 1358-1400.

JÖRESKOG, K. G. and D. SÖRBOM (1984) LISREL VI: Analysis of Linear Structural Relationships by the Method of Maximum Likelihood. Mooresville, IN: Scientific Software.

JÖRESKOG, K. G. and D. SÖRBOM (1986) PRELIS: A Program for Multivariate Data Screening and Data Summarization (A Preprocessor for LISREL), 1st ed. Mooresville, IN: Scientific Software.

JÖRESKOG, K. G. and D. SÖRBOM (1987) LISREL: Analysis of Linear Structural Relationships (User's Guide for LISREL 7). (unpublished)

KENDALL, M. and A. STUART (1979) The Advanced Theory of Statistics, Vol. 2, 4th ed. New York: Charles Griffin.

LONG, J. S. (1983) Confirmatory Factor Analysis. Beverly Hills, CA: Sage.

LONG, J. S. (1987) "A graphic method for the interpretation of multinomial logit analysis." Soc. Methods & Research 15: 420-446.

MADDALA, G. S. (1983) Limited-dependent and Qualitative Variables in Econometrics. Cambridge: Cambridge Univ. Press.

MANSKI, F. C. and D. McFADDEN (eds.) (1981) Structural Analysis of Discrete Data with Econometric Applications. Cambridge: MIT Press.

MARE, R. D. (1980) "Social background and school continuation decisions." J. of the Amer. Stat. Assn. 75: 295-305.

MARE, R. D. and M. D. CHEN (1986) "Further evidence on sibship size and educational stratification." Amer. Soc. Rev. 51: 403-412.

McKELVEY, R. D. and W. ZAVOINA (1975) "A statistical model for the analysis of Ordinal Level Dependent Variables." J. of Mathematical Sociology 4: 103-120.

MISLEVY, R. J. (1986) "Recent developments in the factor analysis of categorical variables." J. of Educ. Statistics 11: 3-31.

MUTHÉN, B. O. (1979) "A structural probit model with latent variables." J. of the Amer. Stat. Assn. 74: 807-811.

MUTHÉN, B. O. (1983) "Latent variable structural equation modeling with categorical data." J. of Econometrics 22: 43-65.

MUTHÉN, B. O. (1984) "A general structural equation model with dichotomous, ordered categorical, and continuous latent variable indicators." Psychometrika 49: 115-132.

MUTHÉN, B. O. (1987) LISCOMP: Analysis of Linear Structural Relations Using a Comprehensive Measurement Model. Mooresville, IN: Scientific Software.

MUTHÉN, B. and D. KAPLAN (1985) "A comparison of some methodologies for the factor analysis of non-normal likert variables." British J. of Mathematical and Stat. Psychology 38: 171-189.

OLSSON, U. (1979) "On the robustness of factor analysis against crude classification of the observations." Multivariate Behavioral Research 14: 485-500.

REVER, P. R. (1973) Scientific and Technical Careers: Factors Influencing Development during the Educational Years. Iowa City, IA: American College Testing Program.

SEWELL, W. H., A. O. HALLER, and A. PORTES (1969) "The educational and early occupational attainment process." Amer. Soc. Rev. 34: 82-92.

SEWELL, W. H. and R. M. HAUSER (1975) Education, Occupation, and Earnings. New York: Academic Press.

SOBEL, M. E., M. HOUT, and O. D. DUNCAN (1985) "Exchange, structure, and symmetry in occupational mobility." Amer. J. of Sociology 91: 359-372.

STEVENS, G. and D. L. FEATHERMAN (1981) "A revised socioeconomic index of occupational status." Social Science Research 10: 364-395.

U.S. Bureau of the Census (1969) Characteristics of America's Engineers and Scientists: 1960 and 1962, technical paper no. 21. Washington, DC: Government Printing Office.

WINSHIP, C. and R. D. MARE (1983) "Structural equations and path analysis for discrete data." Amer. J. of Sociology 89: 54-110.

WINSHIP, C. and R. D. MARE (1984) "Regression models with ordinal variables." Amer. Soc. Rev. 49: 512-525.

XIE, Y. (1988) "The social origins of American scientists." Presented at the Annual Meeting of the American Sociological Association, Atlanta (August).

YAMAGUCHI, K. (1983) "The structure of intergenerational occupational mobility: generality and specificity in resources, channels, and barriers." Amer. J. of Sociology 88: 718-745.

Yu Xie is a doctoral candidate in sociology at the University of Wisconsin-Madison. His research interests include the sociology and history of science, stratification, and quantitative methodology. He is currently completing his dissertation on the recruitment of scientists.