Structural Equation Models with Occupational Choice as the Dependent Variable *

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Structural Equation Models with Occupational Choice as the Dependent Variable

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 and Duncan model, the Wisconsin model, and extended versions of them, 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 unique power of path analysis and structural equations in these models is not to ascertain the total effects of parental characteristics on offspring's status attainment, in terms of reduced form coefficients, but rather to partition the total effects into direct effects and indirect effects through intermediate processes, in terms of structural coefficients. Education, for example, 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, more and more intervening variables have been hypothesized and tested in modeling the causal process of status attainment (for a review see Campbell, 1983).

Despite its enormous success, the approach of path analysis and structural equations has its own weaknesses, one of which is the assumption that dependent variables are continuous and linearly dependent upon predetermined variables. This limitation stems from the fact that structural equations are in essence systems of linear regression equations. It has been well known for a long time that, when dependent variables are discrete rather than continuous, linear models are not appropriate (Hanushek and Jackson, 1977; Maddala, 1983). In practice, researchers in the area of social stratification have traditionally either transformed their discrete dependent variables into continuous variables, such as the Duncan SEI score in Blau and Duncan's analysis, or simply ignored the problem (for example, Sewell and Shah, 1967).

The above mentioned problem has given rise to a renewed interest in analysis of mobility tables and to the methodological innovations in the form of loglinear models (Goodman, 1978; Goodman, 1984; Featherman and Hauser, 1978; Hauser, 1979). This shift in interest is justified by the fact that, if occupational choice is truly discrete, we lose the original meaning of an occupation when we transform occupations into a continuous SEI score or prestige score. Even though classical status attainment research emphasizes occupations as the center of its focus, the method of path analysis and structural equations has stripped much of the unique nature of occupations as opposed to other measures of social status such as earnings and education: its discreteness. The nature of its discreteness implies that the occupational structure is nonlinear and perhaps multi-dimensional.[1] In contrast to path analysis and structural equations, loglinear analysis of mobility tables has the advantage of being flexible enough to take into account the discrete nature of occupations. Moreover, the analysis of mobility tables allows us to investigate the "channels" and "barriers" in the mobility process—to use Blau and Duncan's terminology (1967, p.117)—which

[1] Admittedly, numerous studies of mobility tables have found that distance between father's and son's occupations can be treated as mostly varying along one dimension (for example, Klatzky and Hodge, 1972; Duncan, 1979). However, these studies cannot preclude the possibility that the occupational structure as a whole is multi-dimensional.

are not subject to study within the approach of path analysis and structural equations using socioeconomic or prestige scores. Therefore, "mobility tables are useful" in Hauser's words, because "they tell us where in the social structure opportunities for movement or barriers to movement are greater or less, and in so doing provide clues about stratification processes which are no less important, if different in kind, from those uncovered by multivariate causal models (1978, p.921)." For example, Yamaguchi (1983) explicitly studies "channels" and "barriers" of mobility process using loglinear models of mobility tables.

Unfortunately, loglinear analysis of mobility tables raises further problems. In theory, the discrete coding of occupations contains more information than any occupational score such as SEI, since 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, hinders the meaningful interpretations 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 with the use of Goodman's (1981) statistical tools the loss of information can be minimized, it always requires a strong conviction to believe that occupations within a major occupational category are so homogeneous that people having these occupations can be treated as if they were identical.

Another shortcoming of loglinear analysis of mobility tables is the tendency to neglect intervening factors by devoting full attention to two-way, origin-destination tables. Even though path-analysis-like loglinear models are possible for the analysis of categorical data (for example, Goodman, 1973), they are rarely used in the social stratification literature. This is partly due to 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. This is where econometricians Heckman (1978) and Manski and McFadden (1981) have launched their critique of the pervasive use of loglinear models. To them, loglinear analysis of discrete data is analogous to correlation analysis of continuous data and therefore is incapable of uncovering structural relationships. Manski and McFadden call their own approach the "structural analysis of discrete data." By structural analysis, they mean that independent variables have their unique status—they can be anything, and all of the assumptions that are to be made in modeling pertain to error structure. There is an asymmetry between independent variables and dependent variables. A discrete variable does not pose any problem if it is treated as an independent variable, but it requires special attention and modeling if it is used as a dependent variable.

In the statistical analysis of occupational attainment, for example, it is inconsequential to have family background variables that are discrete. Problems arise when the dependent variables are discrete. Depending on the nature of dependent variables and related assumptions, a number of models have been proposed that are analogous to regression analysis (Maddala, 1983; Amemiya, 1985). Structural equations and path analysis for discrete data have also been proposed (Muthén, 1983; Winship and Mare, 1983; Muthén, 1984), although sociological applications of them have not been seen. Evidently, there is a need for systemization, for better computer packages, and for more illustrative examples before sociologists can apply these methods routinely. The present paper is intended to serve this purpose. It will present structural equations with dichotomous and ordered categorical dependent variables in a more conventional way and introduce a new computer package, LISCOMP, developed by Muthén (1987). Empirical examples are provided in the area where traditional path analysis and structural equation models were first popularized.

The OCG Survey, the Blau-Duncan Model, and Parental Influences

We will present our model using data from the 1962 Occupational Changes in a Generation (OCG) Survey. Being a large national representative sample of the American 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 Blau-Duncan model that was based on it have served as the cornerstone for many later studies of social stratification. The Blau-Duncan model, shown in Figure 1, summarizes Blau and Duncan's basic findings about the way in which father's characteristics affect son's social status. The numbers on the diagram are path coefficients. Son's occupation, son's first job, and father's occupation are recoded into SEI scores. Specifically, Blau and Duncan found that most of father's influence on son's 1962 occupation is mediated by son's education and son's first job. They further assumed that there is no direct effect of father's education (V) on son's first job (W) and on current occupation (Y). In the language of path analysis and structural equations, the paths from V to X and from V to Y are constrained to be zero.

Before proceeding to our analysis with discrete dependent variables, it seems

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Figure 1 About Here
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proper to test and to explore the Blau-Duncan model in its original context. For our data set, we include all 25-64 year old males for whom CPS and OCG files were successfully merged and for whom there are no missing data on the five variables: respondent's 1962 occupation, respondent's first full-time job after school, respondent's education, father's education, and father's occupation. This leaves us with 14401 observations.

To explore the Blau-Duncan model in its original form, we use SEI scores for son's current occupation, son's first job, and father's occupation. We depart from Blau and Duncan, however, by transforming the educational measure from a nine-category variable into a variable that is coded at the mid-point of each interval of years of schooling. The advantage of this transformation over Blau and Duncan's method, which is to use as a continuous variable the numerical codes of zero to eight for levels of education, is that estimated regression coefficients will have a clearer interpretation. We also use Blau and Duncan's notations (Y, W, U, V, X) to denote the variables. Table 1 gives the sample correlation matrix and other simple sample statistics.

An interesting hypothesis that we would like to test against the Blau-Duncan model is that father's occupation may not have a direct affect on son's occupation. The effect of father's occupation may be mediated through son's education, and probably son's first job. Thus, we hypothesize two models, Model 2 and Model 3, in comparison with Model 1, the Blau-Duncan model. In Model 2, we delete the path

Table 1: Correlation Matrix and Other Sample Statistics

Variable	Y	W	U	V	X
Y: Son's Occupation (SEI)	1.000				
W: Son's First Job (SEI)	.543	1.000			
U: Son's Education	.604	.543	1.000		
V: Father's Education	.314	.314	.433	1.000	
X: Father's Occupation (SEI)	.403	.418	.421	.467	1.000
Mean	38.77	26.99	10.96	7.64	27.40
Standard deviation	24.82	21.52	3.55	4.00	21.16

NOTE: Source: 1962 OCG Survey. See text for variable definitions.

Table 2: Comparing the Fit of Three Models of Status Attainment

Model	Description	chi-square	DF
1	Blau-Duncan Model (Figure 1)	5.62	2
2	Deleting path from X to Y	276.97	3
3	Deleting paths from X to Y and W	1199.52	4

NOTE: The sample size is 14401. Chi-square stands for likelihood ratio test statistic reported in LISREL output. DF is the degrees of freedom associated with the chi-square statistic.

from father's occupation (X) to son's occupation (Y). In model 3, we further delete the path from father's occupation (X) to son's first job (W). All three models were estimated using full information maximum likelihood. The results are presented in Table 2.

It is evident that Model 2 and Model 3 must be rejected on statistical grounds.[2] Model 1 is superior to Models 2 and 3, and cannot be rejected, relative to the sat-

[2]For two nested models, we have a chi-square test statistic based on the difference in the likelihood ratio test statistics χ^2 with the degrees of freedom equal to the number of parameters additional in the less restricted model over the more restricted model, given that the more restricted model is true.

Table 3: Estimated Structural Coefficients for Model 1
When Dependent Variables are Continuous

Dependent Variable	W	U	X	V	R-square
	Independent Variables				
U			0.047 (0.001) [0.280]	0.269 (0.007) [0.302]	0.248
W		2.698 (0.045) [0.445]	0.235 (0.008) [0.230]		0.337
Y	0.316 (0.009) [0.275]	2.830 (0.054) [0.405]	0.138 (0.008) [0.117]		0.441

Note: Standard errors are in parentheses. Path coefficients are in brackets. For definition of variables, see text and Figure 1. Estimates were estimated using LISREL. For model fit see Table 2.

urated model, at the 0.05 significance level. Parameter estimates for Model 1 are displayed in Table 3. The standardized estimates, i.e., the path coefficients, are very similar to those estimated by Blau and Duncan. Our reanalysis, therefore, is consistent with the original Blau-Duncan results.

Models of Occupational Choice: Who Becomes Scientists and Engineers?

From the preceding analysis, we know that the Blau-Duncan model works well when we transform occupations into SEI scores. If we want to treat occupations as a discrete variable, we need methods beyond the traditional path analysis approach. In this paper, we treat only two types of discrete variables, dichotomous and ordered polytomous. More general cases will not be covered here. Still, there is a wide range of applications for this kind of model. For example, in studying recruitment into scientific and engineering professions, we want to know how family background affects one's choice to become a scientist or engineer. Here the term "choice" refers one's occupational destination, no matter how he has gotten there.[3] Likewise, we could study the influence of family background on one's propensity to become a businessman. Ordered polytomous variables are also fairly common. In the 1962 OCG Survey, for example, education was asked in terms of nine discrete categories. One could use the numerical codings as a continuous variable as Blau and Duncan did, or transform the variable using the mid-scores as we did in the last section. But a preferred alternative in general is to treat the variable as an ordinal variable and estimate models with an ordered categorical dependent variable.

[3]This usage differs from the narrower, more refined concept of "occupational choice" as only designating aspirations. See Kuvlesky and Bealer (1966).

In the present analysis, our first concern is to consider how family background affects one's life chances of being a scientist or engineer. A study of one's likelihood of becoming a scientist or engineer not only sheds light on the long-standing question how scientists and engineers are different from the general public in their social origins (for a review, see Rever, 1973), but also contributes directly to our understanding of social stratification in general. This is because scientists and engineers constitute a group who enjoy considerable prestige. Their occupational prestige ranking is generally near the top (Duncan, 1961; Stevens and Featherman, 1981). Furthermore, scientists and engineers are a special group whose members have the talents and interests to pursue intellectual and technical careers.[4] In this regard, they are different from other groups of elites such as politicians, lawyers, and physicians. Many studies have found that universalistic criteria dominate science, and there is little evidence of discrimination after functionally relevant factors are taken into account (Cole and Cole, 1973; Merton, 1973; Cole, 1979). Consequently, we have reason to suspect that the pattern of recruitment into scientific and engineering professions is different from the general pattern of social mobility in that family background factors may not persist all the way. We can hypothesize that the likelihood of being a scientist or engineer is the same for people from different backgrounds after educational attainment is controlled. Therefore, we expect some departure from the Blau-Duncan model when the research question is not "what is the general process of status attainment?" which the original model addresses, but instead, "who becomes a scientist or engineer?"

[4]Scientists also exhibit unique personality characteristics, such as the lack of sociability. See Hirsch (1968).

To measure who are scientists, we have a dependent variable, denoted as S, which has two categories. S equals one for scientists and engineers and zero otherwise. The variable S is recoded from detailed 1960 census occupational codes using information provided by the Bureau of the Census as to which codes constitute scientific and engineering occupations (U.S. Bureau of the Census, 1969).[5] For the first job after completing school, we make a similar dichotomous variable F, taking the value of one if first job is in science and engineering and zero otherwise, using the same transformation rules. The means of S and F are 0.036 and 0.017 respectively. Son's education was collapsed from the original nine categories to four categories (0-7, 8-11, 12, and 13+).[6] The same categorization of the education variable is adopted by Winship and Mare (1984) in their analysis of the ordered probit regression using the same data set. To distinguish it from the continuous variable U, we denote the ordered variable measuring son's education as E. The independent variables V and X, however, are unchanged. V is still measured by the mid-points of intervals of years of schooling, and X is father's SEI score. For descriptive statistics on variables S, F, and E, see Table 4.

The Measurement Model

Measurement models, in Jöreskog and Sörbom's LISREL framework, have played an important role in the recent development of structural equation mod-

[5]Specifically, we use the 1960 Census occupational codes 21, 31-53, 80-93, 130-145, and 172-175 to distinguish scientists and engineers from others.

[6]We have experimented with different coding schemes, such as the original nine categories and the two categories (college education versus other). The results are very similar.

Table 4: 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

NOTE: The sample size is 14401.

els. They have brought several statistical tools, i.e., path analysis and structural equations, factor analysis, and reliability analysis, together into a unified approach (Jöreskog and Sörbom, 1984). In this framework, all of the structural relationships, causal or noncausal, are between unobservable latent variables. These latent variables manifest themselves through observed variables. The relationships between latent and observed variables form a "measurement model." For example, if we want to estimate a classical path model without latent variables, we simply let latent variables be identical to the corresponding observed variables.

When all dependent variables are continuous, the traditional way to construct a measurement model is to specify a set of linear regression equations regressing observed on latent variables. One major use of measurement models, in these cases, is to set constraints on the observed variables, thus allowing for testing various hypotheses and assessing measurement error (for examples, see Hauser and Goldberger, 1971; Bielby et al., 1977; Hauser et al., 1983). However, when an observed dependent variable is ordinal (including dichotomous as a special case), the measurement model plays a different role: it links the observed ordinal variable to an unobserved latent continuous variable in a nonlinear way, through a model of thresholds. A measurement model becomes *necessary* in an analysis of ordinal dependent variables.

For the dichotomous dependent variable S, we specify:

$$S_i = 1 \quad \text{if } S_i^* > 0$$

$$S_i = 0 \quad \text{otherwise} \quad (1)$$

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

$$F_i = 1 \quad \text{if } F_i^* > 0$$

$$F_i = 0 \quad \text{otherwise} \quad (2)$$

We can extend the above measurement model to the ordered response case, variable E. Since variable E has four categories, we have the following measurement model:

$$E_i = 3 \quad \text{if } \alpha_3 < E_i^*$$

$$E_i = 2 \quad \text{if } \alpha_2 < E_i^* \leq \alpha_3$$

$$E_i = 1 \quad \text{if } \alpha_1 < E_i^* \leq \alpha_2 \quad (3)$$

$$E_i = 0 \quad \text{if } E_i^* \leq \alpha_1$$

where the α's are threshold parameters defining categorical intervals on E^*. After making this transformation, E^* can be used in very much the same way as a continuous variable. 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

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        Figure 2 About Here
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of E after the assumption of the distributional form on E^* is made. We will not report these estimates.

Clearly, this type of measurement model is different from traditional measurement models in the LISREL framework. Muthén has called it "outer" measurement in comparison with the traditional "inner" measurement. 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 LISREL 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, which is an acronym for the "Analysis of **Li**near **S**tructural Relations Using a **Comp**rehensive Measurement Model."

Assumptions and Normalizations

Our first model shown in Figure 2 is based on Blau-Duncan's basic model. We use squares to indicate observed variables and circles to indicate latent variables. In the diagram we can see a one-to-one correspondence between the observed variables S, F, and E, and their latent counterpart, S^*, F^*, E^*. They form our measurement model. For the structural part, we have the following regression equations:

$$S^* = \beta_{S^*1}1 + \beta_{S^*F^*}F^* + \beta_{S^*E^*}E^* + \beta_{S^*X}X + \epsilon_{S^*}$$
$$F^* = \beta_{F^*1}1 + \beta_{F^*E^*}E^* + \beta_{F^*X}X + \epsilon_{F^*} \quad (4)$$
$$E^* = \beta_{E^*1}1 + \beta_{E^*V}V + \beta_{E^*X}X + \epsilon_{E^*}$$

where the β's are regression coefficients with the first subscript denoting the dependent variable and the second subscript for the regressor, the 1's are intercept terms, and the ϵ's are vectors of error terms. If we assume that the ϵ's are i.i.d (independent and identically distributed) as standardized normal, with the cumulative probability function being $F(z) = \int_{-\infty}^{z} \frac{1}{(2\pi)^{1/2}} exp[-(t^2/2)]dt$, then we have a model with probit regressions (Maddala, 1983; Amemiya, 1985). The variances of the ϵ's are standardized because the scales of latent variables are indeterminate. This is due to the fact that an ordinal variable, of which a dichotomous variable is a special case, does not contain any information about its scale at all. The variances of variables S^*, F^*, and E^* are indeterminate. In conventional structural equation models, normalization can take either of two forms. First, we can standardize (usually to one) either the variance of a latent variable or the variance of the error term when the latent variable is a dependent variable. And alternatively, we can set one of the loadings to a constant (usually to one). In the case of an ordinal variable, loadings are nonlinear and nonstochastically defined in (1)-(3). *In addition*, the variance of the latent variable needs to be normalized. We can either normalize the variances of the latent variables or the variances of the errors. Within the syntax of LISCOMP, we conveniently set the error variances to ones. Because of the one-to-one correspondence in the measurement model (1)-(3), we can also denote the unobserved variable by using an asterisk with the same name as its corresponding observed variable.

Even though logit models are also widely used in the analysis of discrete data, and the choice of probit versus logit model is usually inconsequential for single equation models (Maddala, 1983, p.23), it is necessary to use the probit in structural equation models in order to take account of possible error covariance structure. From now on, we will assume that the error term associated with a latent variable underlying an observed ordinal or dichotomous dependent variable is distributed as a standard normal with a mean of zero and a variance of one.

A distinguishing feature of equation (4) is that neither the independent variables (X and V) nor the latent dependent variables (S^*, F^*, and E^*) are assumed to be normal. Rather, our normality assumption pertains to the distributional form of the error terms. Exogenous variables can be anything. Latent dependent variables are distributed as multivariate normal **conditional** on the predetermined variables. In our model, the error covariances are specified to be zero. More complicated models can contain correlated errors.

Structural Models and Estimation

In the present analysis, we have only one observed variable for each theoretical construct, or only single indicators, to use the language of structural equation models. The "inner" measurement model is unnecessary. With "outer" measurement model (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, we use their underlying latent constructs in relation to all other variables. In some sense the observed ordered variables are left out of the structural model completely. We can conveniently treat the unobserved/observed pair as a single variable. Estimation of equation (4) is made possible after we make the assumptions and normalizations discussed in the preceding section,

The estimation of equation (4) is by no means an easy task despite the simplicity of the model and the related assumptions and normalizations. Full information likelihood estimation is unfeasible at the present time for most models of this kind because of the computational difficulties of integration over the multivariate normal distribution. Instead, Muthén has provided a three-stage limited information GLS (generalized least squares) estimator, which has been programmed in his computer package LISCOMP.

Muthén's GLS gives consistent estimates of the parameters and their standard errors. It also 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 the degrees of freedom equal to the difference in the degrees of freedom between the two models, given that the more restrictive model is correct. By and large, Muthén's GLS performs well (Muthén, 1983; Mislevy, 1986). In the following we will use Muthén's GLS directly without explaining estimation procedures. Readers interested in Muthén's GLS should consult other materials (Muthén, 1983; Muthén, 1984).

The goodness of fit statistic for Model 1 when the dependent variables are dichotomous and ordered polytomous is reported in the first line of Table 5. Estimates of the structural coefficients and their estimated standard errors for Model 1 are given in Table 6.[7] It should be kept in mind, when reading Table 6, that whereas variables V and X have natural scales, given in Table 1, the scales of latent variables S^*, F^*,

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

Table 5: Comparing the Fit of Three Models of the Choosing of Scientific and Engineering Occupations

Model	Description	chi-square	DF
1	Blau-Duncan Model (Figure 2)	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 14401. Chi-square stands for likelihood ratio test statistic reported in LISCOMP output. DF is the degrees of freedom associated with the chi-square statistic.

Table 6: Estimated Structural Probit Coefficients for Model 1, Table 5

Dependent Variable	Independent Variables F*	E*	X	V	R-square
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 definition of variables, see text and Figure 2. Estimates were obtained using LISCOMP. For model fit see Table 5.

and E^* are not defined until we set the error variances to be ones. The variances of S^*, F^*, and E^* are determined by the estimated coefficients and variances of the predetermined variables. For example,

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

where we know that $V(\epsilon_{E^*})$ is normalized to one. From this procedure, our calculation gives: $V(E^*) = 1.41$, $V(F^*) = 1.52$, and $V(E^*) = 1.60$. Once we know the variances of the latent variables, it is easy to calculate R^2's and path coefficients.[8] It should also be noted that these estimates are probit coefficients, interpretations of which can be made in terms of probabilities through nonlinear transformations (Hanushek and Jackson, 1977, p.189).

Overall, Model 1 fits the data well since $\chi^2 = 1.911$ for 2 degrees of freedom. When we look at the estimates, however, we see that two coefficients are estimated to be zeros. This finding supports our hypothesis that recruitment into scientific and engineering professions is mostly based on educational attainment. Family background has its effects, but only through making education more accessible. Controlling for education, the chance of being a scientist or engineer is virtually the same for everyone. To test the hypothesis formally in a different way, we make further restrictions in Model 2 and Model 3, as shown in Table 5. As we expected, deleting paths from X to F^* and E^* does not increase the χ^2 measure much at all. The parsimonious model, Model 3, is therefore retained. The hypothesis that the recruitment process into scientific and engineering occupations is universalistic conditional on educational attainment is confirmed. Table 7 displays the estimated parameters for Model 3. For

[8]For models with exogenous variables, such as those estimated in this paper, it seems impossible to obtain the correct R^2s and path coefficients from standardized solutions reported by LISCOMP 0.1.

a graphic presentation of the final model, see Figure 3.

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Figure 3 About Here

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The final model, shown in Figure 3, represents our finding that the recruitment process into scientific and engineering professions is based on universalistic criteria, i.e., through educational attainment. This conclusion is in accordance with the observation that, compared to other professions, those based on science and technology are among the most likely to have a wider social composition (Elliott, 1972). In other words, scientists and engineers are a group of elites with such unique characteristics that the recruitment process does not favor offspring from high status families after education is controlled for. Therefore, the pattern of intergenerational mobility for scientists and engineers differs from the general pattern observed by Blau and Duncan. Science and engineering provide a more equal arena for competition into higher status than do other spheres of society. Not surprisingly, science and engineering offer great opportunity for the upward mobility of offspring from humble families. The well-known legacies of Faraday and Watt are cases in point.

Another Example: Who becomes Managers, Officials, and Proprietors?

Are scientists and engineers truly unique? Or is our structural equation model with occupational choice as the dependent incapable of detecting the direct effect of family background? In the present section of the paper, we will study another occupational group, namely managers, officials, and proprietors.

Table 7: Estimated Structural Probit Coefficients for Model 3, Table 5

Dependent Variable	Independent Variables F*	E*	X	V	R-square
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 definition of variables, see text and Figure 3. Estimates were obtained using LISCOMP. For model fit see Table 5.

We define managers, officials, and proprietors according to the census occupational codes. Farmers are excluded.[9] Like scientists and engineers, managers, officials, and proprietors in general have high social status (Duncan, 1961; Blau and Duncan, 1967). The recruitment process into these occupations, however, should be different from that into science and engineering. In fact, the intergenerational mobility pattern for managers, officials, and proprietors should not be much different from the general one observed by Blau and Duncan. That is, the effect of family background should persist beyond educational attainment. This is because high status families have more economic resources and social networks which can assist their offspring to have successful careers as managers, officials, or proprietors. In addition, a child from a high status family generally has better communication skills and has been exposed to a wider world. This is in contrast with the fact that eminent scientists are often portrayed as having had isolated childhoods (Hirsch, 1968). These advantages accumulate and affect one's chances of success as a manager, official, or proprietor. Given the same amount of education, a child from a humble family faces more barriers to success. Since 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 being a manager, official, and proprietor.

The procedure for testing our hypothesis is similar to what we did in the last section. We define a dichotomous variable B. B is equal to one if the respondent is in the occupations of managers, officials, and proprietors, and zero otherwise. Similarly,

[9] In terms of the 1960 Census occupational codes, our definition includes 250 to 290.

Table 8: Comparing the Fit of Three Models of the Choosing to be Managers, Officials, and Proprietors

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 14401. Chi-square stands for likelihood ratio test statistic reported in LISCOMP output. DF is the degrees of freedom associated with the chi-square statistic.

T equals one if his first job is in these occupations and zero otherwise. B and T have means of 0.157 and 0.018 respectively. Since B and T are dichotomous dependent variables, we have the latent variables B^* and T^*. We retain the four-category coding of son's education E and its latent construct E^*. Father's education U and father's occupational SEI score X remain unchanged. We will estimate the three structural models that we have run when the likelihood of becoming a scientist or engineer was the dependent variable. The test statistic of model fitness is reported in Table 8.

It is evident from Table 8 that the Blau-Duncan model holds well for modeling the process of becoming managers, officials, and proprietors. Father's occupational status affects not only son's' educational attainment, but also son's likelihood to become a manager, official, and proprietor at first job and current job. The effect of family background is mediated through son's education, but not entirely. The direct effects of father's occupational status on both son's first job and current job are statistically significant. Looking at the estimated coefficients in Table 9, we can see that all the coefficients are positive and statistically significant from zero, confirming our hypothesis that offspring from high status families are more likely to

Table 9: Estimated Structural Probit Coefficients of Model 1, Table 8

Dependent Variable	T*	E*	X	V	R-square
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 definition of variables, see text. Estimates were obtained using LISCOMP. For model fit see Table 8.

become managers, officials, and proprietors even given the same amount of education. This result is consistent with Yamaguchi's (1983) finding that education explains the effect of father's occupation on the likelihood of becoming professionals, but not the likelihood of becoming managers, officials, and proprietors. We also notice that the path coefficients of E^* on T^* and B^* are smaller than those in Table 7. This suggests that education is a less powerful determinant for the recruitment process into managers, officials, and proprietors than for that into science and engineering. As a consequence, the R^2's are smaller than those in our structural equation models for scientists and engineers.

Conclusion

Our analysis of the recruitment process into science and engineering, and of that into managers, officials, and proprietors, has demonstrated how one can study occupational choice using the structural equations approach. It has been shown that different occupations may have different recruitment patterns, suggesting that the occupational structure is nonlinear and multi-dimensional. By focusing on entries into particular occupations, we increase our knowledge of how social mobility operates through various "channels." Science and engineering, for example, was shown to be a fair arena of competition where universalistic criteria dominate. There, parental characteristics effect one's chance to become a scientist or engineer only indirectly, by making education more accessible. On the other hand, one's chances of becoming a manager, official, or proprietor are largely dependent on father's social status after education is controlled.

The structural equations approach outlined in this paper has the advantage of taking several variables into account simultaneously. Total effects are partitioned into direct effects 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. Our structural models of occupational choice are also an advance over traditional path analysis and structural equations in the LISREL framework. Ordered polytomous variables and dichotomous need not be transformed into continuous variables on an arbitrary basis. We can study the conditional probability of discrete dependent variables in a set of structural equations. In short, the aim of our new approach is to bring discrete dependent variables into structural equation models.

This aim has not been completely satisfied. So far, we have dealt only with dichotomous and ordered polytomous variables. The more general case of unordered polytomous dependent variables cannot be handled using our approach. They need to be analyzed with loglinear models or various logit models (Bishop et al., 1975; Maddala, 1983). Another limitation of our model is the assumption that there is a continuous variable underlying discrete observed variable through the measurement model of a threshold. The measurement model of a threshold may not be appropriate in all cases. In our examples, dichotomizing population into scientists and engineers versus others makes sense since scientists and engineers represent a group of people with unusual talents and interests in pursuing scientific and engineering careers. It is also reasonable to assume that managers, officials, and proprietors possess certain unique characteristics as compared to others. It would make little sense to assume that bus drivers are a distinct group that exceed a threshold on a continuous variable, since many bus drivers can have alternative jobs with little hesitation and little difficulty. The fact that they are bus drivers only tells us what they happen to do, not that they have exceeded a threshold. The final limitation of our model is that we can only deal with one occupation at a time. This is because occupations are not necessarily unidimensional, and we cannot assume that occupations form an ordered variable. In our examples, we avoided this problem by considering two occupational choices separately. This solution has a heuristic value. But we cannot formally combine the results from two studies together because the categorical divisions of dependent variables overlap. We need to limit ourselves to one question at a time.

Nevertheless, our model of occupational choice in structural equations opens up more research areas and offers alternative research methods. In one sense, it is a natural extension of structural equation models and probit analysis. The limitations listed in the last paragraph also apply to probit models. As long as the researcher knows when a probit model is appropriate, the incorporation of probit models into structural analysis can expand our ability to analyze data. With the recent sophistication of the computer program LISCOMP, more sociological application of structural equations with discrete dependent variables should be seen in the near future.

REFERENCES

Amemiya, Takeshi. 1985. *Advanced Econometrics.* Cambridge, Mass: Harvard University Press.

Bielby, William 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, Conn.: JAI Press, Inc.

Bielby, William T., Robert M. Hauser, and David L. Featherman. 1977. "Response Errors of Black and Nonblack Males in Models of the Intergenerational Transmission of Socioeconomic Status." *American Journal of Sociology* 82:1242-88.

Bishop, Yvonne M.M., Stephen E. Fienberg, and Paul W. Holland. 1975. *Discrete Multivariate Analysis: Theory and Practice.* Cambridge, Mass.: MIT Press.

Blau, Peter M., and Otis Dudley Duncan. 1967. *The American Occupational Structure.* New York: Wiley and Sons.

Campbell, Richard T. 1983. "Status Attainment Research: End of the Beginning or Beginning of the End?" *Sociology of Education* 56:47-62.

Cole, Jonathan. 1979. *Fair Science: Women in the Scientific Community.* New York: Free Press.

Cole, Jonathan, and Steven Cole. 1973. *Social Stratification in Science.* Chicago: University of Chicago Press.

Duncan, Otis Dudley. 1961. "A Socioeconomic Index for all Occupations." Pp. 109-38 in Albert J. Reiss, Jr. (ed.), *Occupations and Social Status.* New York: Free Press.

Duncan, Otis Dudley. 1979. "How Destination Depends on Origin in the Occupational Mobility Table." *American Journal of Sociology* 84:793-803.

Duncan, Otis Dudley, David L. Featherman and Beverly Duncan. 1972. *Socioeconomic Background and Achievement.* New York: Academic Press.

Elliott, Philip. 1972. *The Sociology of the Professions.* London: MacMillan.

Featherman, David 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: Sage.

Featherman, David L., and Robert M. Hauser. 1978. *Opportunity and Change.* New York: Academic Press.

Goodman, Leo A. 1973. "Causal Analysis of Data from Panel Studies and Other Kinds of Surveys." *American Journal of Sociology* 78:1135-91.

Goodman, Leo A. 1978. *Analyzing Qualitative/Categorical Data: Log-Linear Models and Latent-Structure Analysis.* Cambridge, Mass.: Abt Books.

Goodman, Leo 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." *American Journal of Sociology* 87:612-50.

Goodman, Leo A. 1984. *The Analysis of Cross-Classified Data Having Ordered Categories.* Cambridge: Harvard University Press.

Hanushek, Erik A., and John E. Jackson. 1977. *Statistical Methods for Social Sciences.* New York: Academic Press.

Hauser, Robert M. 1978. "A Structural Model of the Mobility Table." *Social Forces* 56:919-953.

Hauser, Robert 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, Robert M., and Arthur S. Goldberger. 1971. "The Treatment of Unobservable Variables in Path Analysis." Pp. 81-117 in Herbert L. Costner (ed.) *Sociological Methodology, 1971.* San Francisco: Jossey Bass.

Hauser, Robert M., Shu-Ling Tsai, and William H. Sewell. 1983. "A Model of Stratification With Response Error in Social and Psychological Variables." *Sociology of Education* 56:20-46.

Heckman, James J. 1978. "Dummy Endogenous Variables in a Simultaneous Equation System." *Econometrica* 46:931-959.

Hirsch, Walter. 1966. *Scientists in American Society.* New York: Random House.

Jöreskog, Karl, and Dag Sörbom. 1984. *LISREL VI: Analysis of Linear Structural Relationships by the Method of Maximum Likelihood.* Mooresville, IN: Scientific Software, Inc.

Klatzky, Sheila R., and Robert W. Hodge. 1971. "A Canonical Correlation Analysis of Occupational Mobility." *Journal of the American Statistical Association* 66:16-22.

Kuvlesky, William P. and Robert C. Bealer. 1966. "A Clarification of the Concept 'Occupational Choice'. " *Rural Sociology* 31:265-276.

Maddala, G. S. 1983. *Limited-dependent and Qualitative Variables in Econometrics.* Cambridge: Cambridge University Press.

Manski, F. Charles, and Daniel McFadden. 1981. (eds) *Structural Analysis of Discrete Data with Econometric Applications.* Cambridge: The MIT Press.

Merton, Robert K. 1973. *The Sociology of Science: Theoretical and Empirical Investigations.* Chicago: University of Chicago Press.

Mislevy, Robert J. 1986. "Recent Developments in the Factor Analysis of Categorical Variables." *Journal of Educational Statistics* 11:3-31.

Muthén, Bengt O. 1983. "Latent Variable Structural Equation Modeling with Categorical Data." *Journal of Econometrics* 22:43-65.

Muthén, Bengt O. 1984. "A General Structural Equation Model with Dichotomous, Ordered Categorical, and Continuous Latent Variable Indicators." *Psychometrika* 49:115-132.

Muthén, Bengt O. 1987. *LISCOMP: Analysis of Linear Structural Relations Using a Comprehensive Measurement Model.* Mooresville, IN: Scientific Software, Inc.

Rever, Philip R. 1973 . *Scientific and Technical Careers: Factors Influencing Development during the Educational Years.* The American College Testing Program.

Sewell, William H. and Robert M. Hauser. 1975. *Education, Occupation, and Earnings.* New York: Academic Press.

Sewell, William H. and Vimal P. Shah. 1967. "Socioeconomic Status, Intelligence, and the Attainment of Higher Education. *Sociology of Education* 40:1-23.

Sewell, William H., Archibald O. Haller, and Alejandro Portes. 1969. "The Educational and Early Occupational Attainment Process." *American Sociological Review* 34:82-92.

Stevens, Gillian, and David L. Featherman. 1981. "A Revised Socioeconomic Index of Occupational Status." *Social Science Research* 10:364-95 .

U.S. Bureau of the Census. 1969. *Characteristics of America's Engineers and Scientists: 1960 and 1962*, Technical Paper No. 21. Washington, D.C.: U.S. Government Printing Office.

Winship, Christopher, and Robert D. Mare. 1983. "Structural Equations and Path Analysis for Discrete Data." *American Journal of Sociology* 89:54-110.

Winship, Christopher, and Robert D. Mare . 1984. "Regression Models with Ordinal Variables." *American Sociological Review* 49:512-25.

Yamaguchi, Kazuo. 1983. "The Structure of Intergenerational Occupational Mobility: Generality and Specificity in Resources, Channels, and Barriers." *American Journal of Sociology* 88:718-745.

APPENDIX: AN EXAMPLE OF CONTROL FILES IN LISCOMP

The following LISCOMP control file was used to estimate Model 1 of Table 5. The estimated coefficients are reported in Table 6.

```
=====================================================================

TI     BLAU-DUNCAN MODEL: CHOICE TO BE 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)

=====================================================================
```

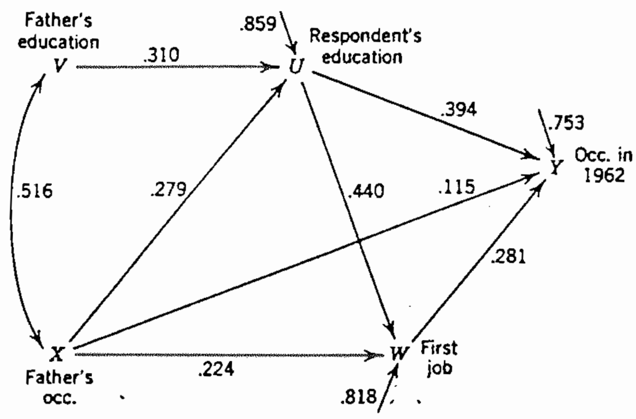

Figure 1. Path coefficients in basic model of the process of stratification. (from Blau and Duncan, 1967, p.170)

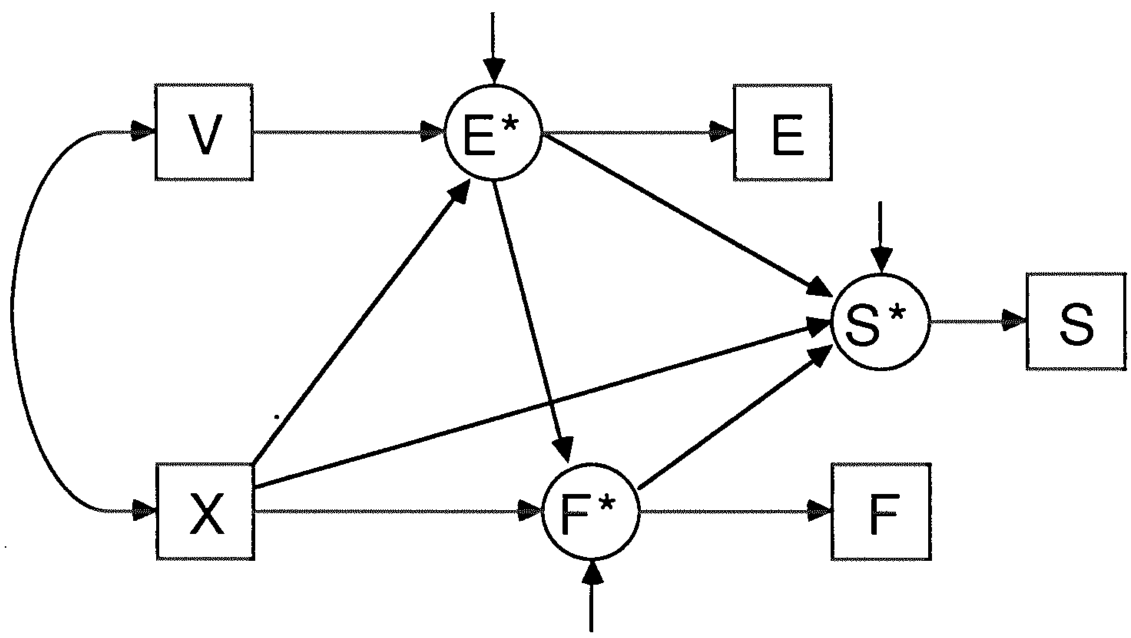

Figure 2: Structural Modeling of the Occupational Choice
To Become a Scientist or Engineer, Model 1

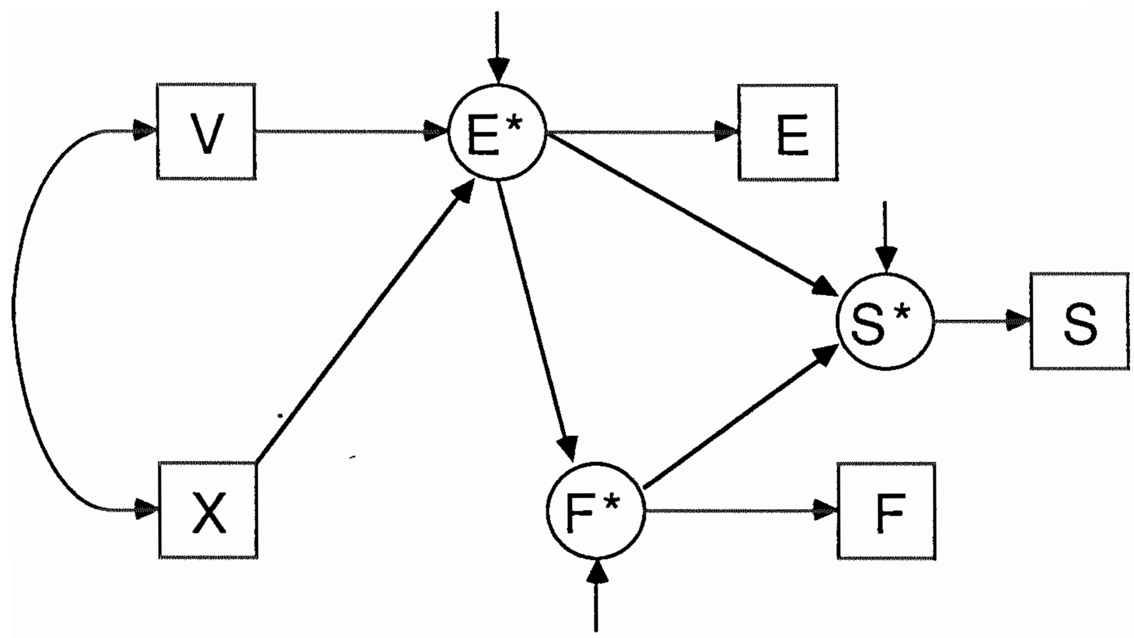

Figure 3: Structural Modeling of the Occupational Choice
To Become a Scientist or Engineer, Model 3