Social Mobility and Fertility Revisited: Some New Models for the Analysis of the Mobility Effects Hypothesis

Author(s): Michael E. Sobel
Source: *American Sociological Review*, Vol. 50, No. 5 (Oct., 1985), pp. 699-712
Published by: American Sociological Association
Stable URL: https://www.jstor.org/stable/2095383
Accessed: 19-12-2019 11:10 UTC

RESEARCH NOTE

SOCIAL MOBILITY AND FERTILITY REVISITED: SOME NEW MODELS FOR THE ANALYSIS OF THE MOBILITY EFFECTS HYPOTHESIS*

MICHAEL E. SOBEL
University of Arizona

Previous designs for the analysis of the mobility effects hypothesis do not incorporate explanatory variables other than origins, destinations, and mobility, and most designs fail to parametrize the effects of origins and destinations in a substantively defensible fashion. Sobel (1981) proposed a class of models for the analysis of mobility effects that parametrizes the effects of origins and destinations in a sociologically meaningful fashion, but his models do not allow for the introduction of explanatory variables other than mobility. This paper shows how to incorporate covariates into the models proposed by Sobel, thereby allowing for a better assessment of the mobility effects hypothesis. Estimation of the new models is discussed, and the relationship between social mobility and fertility as previously considered by Blau and Duncan (1967), is reexamined. Although this reexamination largely confirms the negative results obtained by Blau and Duncan (1967) on mobility effects, the models proposed here also yield previously unobtainable conclusions about the relative import of various origin and destination categories in the acculturation process and the differential impact of various explanatory variables. The relative impact of origins and destinations on fertility depends upon origin status; for example, origins and destinations are equally important among those with farm origins, but origin status is more central than destination status among those with higher white-collar origins. Also, the impact of the explanatory variables on fertility interacts with origin status.

The idea that social mobility is linked to a variety of social behaviors and psychological states goes back at least to Dumont (1890), who argued that small family size is conducive to upward social mobility. More recent versions of the mobility effects hypothesis have regarded various aspects of social and psychological functioning as an outcome of the mobility process (Berent, 1952; Riemer and Kiser, 1954; Stone, 1952; Tien, 1961), and several theoretical reasons for this presumed link have been offered (Blau, 1956; Sorokin, 1927; Westoff, 1953; Freedman, 1963; Easterlin, 1975; Halaby and Sobel, 1979). In these versions of the hypothesis, a social or psychological outcome of interest is jointly explained by 1) a socialization or acculturation process, as represented by the additive effects of origins and destinations, and 2) the net impact of mobility on the outcome (Duncan, 1966; Blau and Duncan, 1967; Sobel, 1981). Mobility effects, then, capture that which remains after the baseline socialization (acculturation) process has been taken into account.

To date, the bulk of the evidence appears to indicate that mobility per se does not effect attitudes and behaviors (for a few representative examples see Laslett, 1971; Knoke, 1973; Jackman, 1972; Kessin, 1971; Jackson and Curtis, 1972; Curtis and Jackson, 1977; Blau and Duncan, 1967). This has encouraged researchers to speculate on the reasons why mobility effects should not exist. For example, Wilensky (1966) argues that mobility effects should not occur when individuals are status inconsistent, as failures in one aspect of life are balanced by success in at least one other. Goldthorpe (1980) suggests that mobility effects are less likely to exist when mobility is a

*Direct all correspondence to Michael E. Sobel, Department of Sociology, University of Arizona, Tucson, AZ 85721

I would like to thank Gerhard Arminger, Clifford C. Clogg, Richard F. Curtis, Otis Dudley Duncan, Christopher Flinn, Neil Fligstein, Robert Mare, Mark Reiser, I. Richard Savage, and an anonymous reviewer for helpful comments and advice.

prevalent phenomenon, while Curtis and Jackson (1977:145) argue that "social arrangements and cultural prescriptions" can mitigate the stressful effects of mobility. Halaby and Sobel (1979) argue that mobility effects are less likely to exist in some types of rank systems than others. Seeman (1977) questions the assumptions about status that underly mobility effect hypotheses, arguing that sociologists should reconsider their convictions about the salience of status change in human life.

Despite this body of negative evidence and theorizing, there are several reasons why Seeman's suggestion is premature. The theoretical arguments against the mobility effects hypothesis are more appropriately regarded as useful elaborations of the hypothesis, and not as a wholesale condemnation of the hypothesis itself. By suggesting the structural conditions under which mobility effects should and should not be found, these arguments do not attack the basic premises of the theory—rather, they lend specificity to the hypothesis that mobility affects social and psychological functioning. Second, almost all previous investigators have used either the square–additive (Blau and Duncan, 1967) or diamond–additive (Hope, 1975) ANOVA models in empirical work, and there are several serious problems with these models.

As Sobel (1981) demonstrated, both models fail to parametrize the origin and destination effects in a manner that yields a reasonable representation of the baseline acculturation process. Further, researchers using these models typically consider only three classes of explanatory variables: origin status, destination status, and mobility. This is a serious limitation, and it is important to allow for the inclusion of other explanatory variables. The net effect of mobility on an outcome of interest has not been properly assessed in previous work, rendering previous evidence on the mobility effect hypothesis unconvincing.

To correct for the deficiencies of the square–additive and diamond–additive ANOVA models, Sobel (1981) proposed a class of models for the analysis of mobility effects (diagonal mobility models) in which the baseline acculturation process is meaningfully parametrized.[1] Unlike the square and diamond additive models, Sobel's model also permits an assessment of the relative impact of origins and destinations on the phenomenon under consideration. This allows, under certain conditions, for adjudication among hypotheses that contend or imply that adult socialization is unimportant, vis-à-vis early socialization (Lewis, 1966; Langner and Michael, 1963; Liem and Liem, 1978) and hypotheses that argue the importance of continuing socialization (Kohn, 1977; Levinson et al., 1978). Thus, Sobel's model can be used to address related theories as well, though the only types of explanatory variables considered by Sobel are origin status, destination status, and mobility. As it is unclear how to incorporate other explanatory variables into his diagonal models, those models are also of limited utility.

The primary purpose of this paper is to indicate how the diagonal mobility models may be expanded to allow for the introduction of other explanatory variables. After a brief review of the diagonal mobility model, the incorporation of other explanatory variables (covariates) into this model in a general and meaningful way is shown. Various special cases of the new model are considered and the relationship between these special cases, the diagonal models proposed by Sobel, and the general linear model is indicated. A reconsideration of the relationship between mobility and fertility, using data from the 1962 Occupational Changes in a Generation (OCG-I) survey, illustrates the proposed models. Limitations of the model are discussed in the concluding section, and further theoretical and methodological developments are also suggested. In particular, it is suggested the models discussed here are applicable in a variety of research contexts.

DIAGONAL MOBILITY MODELS WITH COVARIATES

Consider the square mobility table with R rows (origin states) and columns (destination states), and let Y be a continuous random variable that depends on both the row variable (O) and the column variable (D). Suppose now that a sample is drawn, and for each observation, the values of Y, O, and D observed are recorded. Letting $i, i=1, \ldots, R$, index the level of O recorded, and $j, j=1, \ldots, R$, the level of D recorded, let y_{ijk} denote the value of the dependent variable taken by the (k)th observation from the (ij)th cell of the mobility table, i.e., from the (ij)th level of the joint variable (O,D). The usual additive analysis of variance (ANOVA) model that corresponds to this setup is given as (Winer, 1972):

$$y_{ijk} = \mu_{ij} + \epsilon_{ijk}, \quad (1)$$

$$\mu_{ij} = \mu + \alpha_i + \beta_j, \quad (2)$$

where μ_{ij} is the mean value of the random variable Y for observations drawn from the (ij)th cell of the mobility table, ϵ_{ijk} is an

[1] These diagonal models should not be confused with the diagonal models considered by Goodman (1972).

observation-specific disturbance term with mean O and variance σ^2, μ is the population mean of the random variable Y, and α_i and β_j are, respectively, the effect of origin status i on Y and the effect of destination status j on Y.

Although many previous investigators used the model above to represent the baseline model of acculturation, Hope (1975) and Sobel (1981) show that such usage is inappropriate. Sobel (1981) suggests several alternatives. The simplest of these is the simple diagonal ANOVA model:

$$y_{ijk} = \mu_{ij} + \epsilon_{ijk}, \quad (3)$$
$$\mu_{ij} = p\mu_{ii} + r\mu_{jj}, \quad (4)$$
$$p + r = 1, \quad (5)$$
$$p \text{ lies in the closed interval } [0,1], \quad (6)$$

where, as before, μ_{ij} is the population mean of the observations drawn from the (ij)th cell of the mobility table, and ϵ_{ijk} is a disturbance term with mean 0 and variance σ^2.

Comparison of equations (1) and (2) with equations(3)–(6) reveals that the conceptual difference between the usual ANOVA model and the simple diagonal ANOVA model hinges on the manner in which μ_{ij} is decomposed. In the usual ANOVA model, μ_{ij}, the average behavior of a randomly-selected observation from the (ij)th cell of the mobility table, is the sum of an overall effect (μ), an origin effect (α_i) that applies to all observations from the (i)th origin state, and a destination effect (β_j) that applies to all observations from the (j)th destination state. In contrast, in Sobel's model, μ_{ij} is a weighted average of an effect (μ_{ii}) that applies to all observations from the (i)th origin state and an effect (μ_{jj}) that applies to all observations from the (j)th destination state.

In substantive terms, under Sobel's model, μ_{ij}, the average behavior of a randomly-selected individual who, between time one and time two, moves from origin status i to destination status j, is a weighted average of μ_{ii} and μ_{jj}, the population means of those who remained, respectively, in statuses i and j at both time points under consideration. Thus, individuals who change status have two referent or target values, μ_{ii}, which characterize the average response of such individuals had they stayed in origin status i, and μ_{jj}, the average response such individuals would give if they had been in origin status j at time one. Under the model, all individuals who move out of any state weight the two referent values by an origin parameter p and a destination parameter r ($r=1-p$), where equations (5) and (6) insure the interpretation of these parameters as weights. The mean, μ_{ij}, is thus a weighted average of these two referent values, and the weight, p, indicates the relative salience of the referent value μ_{ii} vis-à-vis μ_{jj}. Values of p greater than .5 indicate that socialization, both prior and ongoing, to the behavior that typifies status i is more important than socialization to the behavior that typifies status j, while values less than .5 indicate the opposite. Finally, individuals who do not change their status are characterized by one and only one of the referent values μ_{ii}, $i=1,\ldots, R$ (since the model implies $y_{iik} = \mu_{iik} +_{iik}$).[2]

Two extensions of the simple diagonal ANOVA model are also considered by Sobel. A diagonal ANOVA model (without mobility effects) is given by:

$$y_{ijk} = \mu_{ij} + \epsilon_{ijk}, \quad (7)$$
$$\mu_{ij} = p_i\, \mu_{ii} + r_i\, \mu_{jj}, \quad (8)$$
$$p_i + r_i = 1,\ i = 1,\ldots,R, \quad (9)$$
$$p_i \text{ lies in the closed interval } [0,1],\ i = 1,\ldots,R. \quad (10)$$

Note that the only difference between the simple diagonal ANOVA model and the model given by equations (7)–(10) is that, in the latter, the weights p and r are replaced by new weights p_i and r_i that are allowed to vary across origin statuses. That is, under equations (7)–(10), the relative salience of socialization to origin and destination statuses is allowed to vary over origin statuses, whereas this is not the case under the simple diagonal ANOVA model. Otherwise, the simple diagonal ANOVA model and the model given by equations (7)–(10) are conceptually identical.

The second extension considered by Sobel is the model:

$$y_{ijk} = \mu_{ij} + \epsilon_{ijk}, \quad (11)$$
$$\mu_{ij} = p_j\, \mu_{ii} + r_j\, \mu_{jj}, \quad (12)$$
$$p_j + r_j = 1,\ j = i,\ldots,R, \quad (13)$$
$$p_j \text{ lies in the closed interval } [0,1],\ j = 1,\ldots,R, \quad (14)$$

where, as before, ϵ_{ijk} has mean 0 and variance σ^2. Ostensibly, the only difference between the model (7)–(10) and the model (11)–(14) is the replacement of origin weights by destination weights. However, it should be the case that if $i=j$, $p_i=1-p_j$. Thus, this new model appears to be redundant. Nevertheless, this model is considered because it need not be the case that, if $i=j$, $\hat{p}_i=1-\hat{p}_j$, where $\hat{p}_i$ and $\hat{p}_j$ are sample estimates of $\hat{p}_i$ and $\hat{p}_j$, respectively.[3]

The diagonal models above omit both mobility effects and other potential effects. Mobility effects are easily incorporated into these models by including appropriate terms for these in equations (4), (8), and (12). For example, if mobility effects are present in the model

[2] A more detailed substantive justification and derivation of this model is given by Sobel (1981).

[3] This is really an estimation issue; discussion of this issue will be temporarily postponed.

(7)–(10), equation (8) may be modified as follows:

$$\mu_{ij} = p_i\mu_{ii} + r_i\mu_{jj} + \sum_{w=1}^{W} \gamma_w M_{ijw}, \qquad (15)$$

where the M_{ijw}, $w=1,\ldots,W$, are mobility variables (for example, upward vs. downward contrasts, mover–stayer contrasts, or the number of steps moved through the mobility hierarchy). Note that M_{ijw} is not subscripted with k terms, as all observations in a particular cell have identical values on the mobility variables. Note also that it is not necessary to modify the interpretation of the other parameters in the presence of mobility effects.

Strategies for the incorporation of other explanatory variables (covariates) into the models above are less obvious. The need for such an extension should be clear, however. To see this, consider the case of a randomly-selected observation k from the (i)th diagonal cell of the mobility table, $i=1,\ldots, R$. Under any of the diagonal models, this observation is assumed to be drawn from a probability distribution with mean μ_{ii} and variance σ^2, and the structural model for such observations reduces to

$$y_{iik} = \mu_{ii} + \epsilon_{iik}. \qquad (16)$$

Under the simplistic assumptions made thus far, all diagonal variability in the response variable is attributable solely to unobservable random influences, and not to various explanatory variables.

A structural model that allows for the inclusion of covariates may be obtained simply by replacing the quantities μ_{ij}, μ_{ii}, and μ_{jj} in the diagonal models by analogous types of quantities μ_{ijk}, μ_{iik}, and μ_{jjk} that are allowed to depend upon various explanatory variables. To obtain such quantities, a structural model is proposed for observations drawn from each diagonal cell of the mobility table.

For observations from the (i)th diagonal cell, $i=1,\ldots,R$, the following linear regression model is proposed:

$$y_{iik} = \mu_{iik(ii)} + \epsilon_{iik}, \qquad (17)$$

$$\mu_{iik(ii)} = \alpha_i + \sum_{l=1}^{L} \beta_{il} X_{iikl}, \qquad (18)$$

where $\mu_{iik(ii)}$ is the mean of the (k)th observation drawn from the (i)th diagonal cell, X_{iikl} is the value of the (l)th explanatory variable ($l=1,\ldots L$) taken by the (k)th observation from the (i)th diagonal cell, α_i and β_{il}, $l=1,\ldots, L$, are a set of parameters specific to the (i)th diagonal cell, and the other elements are as previously described.[4] Under this formulation, for those who are in both origin and destination state i, the model underlying the response variable is a linear regression model, with conditional expectation $\mu_{iik(ii)}$, explanatory variables $X_{iik1},\ldots,X_{iikL}$, and parameters α_i, $\beta_{i1},\ldots, \beta_{iL}$, and σ^2; α_i will hereafter be referred to as an intercept.

Equations (17) and (18) provide the bases for obtaining a general diagonal model with covariates. For an observation k from the (ij)th cell of the mobility table, with $i\neq j$, we now define two new quantities:

$$\mu_{iik(ij)} = \alpha_i + \sum_{l=1}^{L} \beta_{il} X_{ijkl}, \qquad (19)$$

and

$$\mu_{jjk(ij)} = \alpha_j + \sum_{l=1}^{L} \beta_{jl} X_{ijkl}, \qquad (20)$$

where X_{ijkl} is the value of the (l)th explanatory variable ($l=1,\ldots,L$) taken by the (k)th observation from the (ij)th cell, and the other notation is as previously described. Conceptually, $\mu_{iik(ij)}$ and $\mu_{jjk(ij)}$ are analogous, respectively, to μ_{ii} and μ_{jj} in the diagonal ANOVA models previously considered. To see this, note that if no explanatory variables are included in equations (19) and (20), $\mu_{iik(ij)}$ reduces to $\alpha_i = \mu_{ii}$, and $\mu_{jjk(ij)}$ reduces to $\alpha_j = \mu_{jj}$.

A general analogue to each of the diagonal ANOVA models may now be defined. For example, the general analogue to the model specified in equations (7)–(10) is given by:

$$y_{ijk} = \mu_{ijk} + \epsilon_{ijk}, \qquad (21)$$

$$\mu_{ijk} = p_i\,\mu_{iik(ij)} + r_i\,\mu_{jjk(ij)}, \text{ where}$$

$$\mu_{iik(ij)} = \mu_{jjk(ij)} \text{ if } i=j,$$

$$\mu_{iik(ij)} = \alpha_i + \sum_{l=1}^{L} \beta_{il} X_{ijkl}, \qquad (22)$$

$$p_i + r_i = 1,\ i = 1,\ldots,R, \qquad (23)$$

p_i lies in the closed interval [0,1], $i=1,\ldots,R$. (24)

---

[4] At this point, the notation k(ij) is introduced to index the (k)th observation in the (ij)th cell of the mobility table. Although this notation appears to be redundant in the context of equations (17) and (18), its subsequent utilization is not; to see this simply compare the expression $\mu_{iik(ii)}$ with $\mu_{iik(ij)}$, which is defined momentarily. Note also that by complicating the notation further, both the explanatory variables and the number of these could explicitly be allowed to differ across the R diagonal cells. Technically, however, this complication is not necessary, for by defining the set of explanatory variables appropriately, any case of the form above may be written as in (18).

Note that under this formulation, μ_{ijk} is now defined in terms of $\mu_{iik(ij)}$ and $\mu_{jjk(ij)}$, whereas in the diagonal ANOVA models, μ_{ij} was defined in terms of μ_{ii} and μ_{jj}.

From the formulation above it follows (by substitution) that

$$y_{ijk} = p_i\,(\alpha_i + \sum_{l=1}^{L} \beta_{il}\, X_{ijkl}) + r_i\,(\alpha_j + \sum_{l=1}^{L} \beta_{jl} X_{ijkl}) + \epsilon_{ijk} \quad (25)$$

under this particular version of the general baseline model. Substantively, the only difference between the baseline model (7)–(10) and the general baseline model (21)–(24) is that the former model only allows for the mean effects of origins and destinations, whereas the latter model allows for both these effects and those of other explanatory variables. Under the general baseline model, individuals who change status are characterized by two referent values, $\mu_{iik(ij)}$ and $\mu_{jjk(ij)}$, and these referent values are now allowed to depend causally on one or more explanatory variables.[5] The interpretation of the weight parameters is identical under the model (7)–(10) and the model (21)–(24), and the individual responses are determined by the same averaging process in both cases. Similarly, mobility effects are easily included into any particular version of the general baseline model by incorporating the terms $\sum_{w=1}^{W} \gamma_w M_{ijw}$, as previously defined. into the appropriate equations. For example, under the model (21)–(24), these terms are added to equation (22). Equation (25) then becomes:

$$y_{ijk} = p_i\,(\alpha_i + \sum_{l=1}^{L} \beta_{il}\, X_{ijkl}) + r_i\,(\alpha_j + \sum_{l=1}^{L} \beta_{jl}\, X_{ijkl}) + \sum_{w=1}^{W} \gamma_w M_{ijw} + \epsilon_{ijk}; \quad (26)$$

[5] In many applications the explanatory variables either do not change values between times one and two, or such a change is irrelevant. In some instances, however, one might want to allow for explanatory variables that vary. Although this situation is not discussed further in this paper, the model could be modified to allow for this possibility in a substantively meaningful way.

equation (26), along with (22)–(24), suffices to define one version of the general diagonal mobility model with mobility effects included.[6]

The models given by (21)–(24) and (26) with (23)–(24) are very general, and subsume many special cases of substantive interest. Several of these are:

1) both weights and intercepts depend on origins and/or destinations, but the other parameters do not;
2) both weights and intercepts depend on origins and/or destinations, and the other parameters vanish, excepting the parameter σ^2;
3) intercepts depend on origins and/or destinations, but the other parameters do not;
4) intercepts depend on origins and/or destinations, and the other parameters vanish, excepting the parameter σ^2;
5) weights depend on origins and/or destinations, but the other parameters do not;
6) neither the weights, the intercepts, nor the other parameters depend on origins and/or destinations.

To obtain and understand these special cases, we may consider, without loss of generality, equations (21)–(24). To obtain case 1), simply rewrite $\mu_{iik(ij)}$ of equation (22) as:

$$\mu_{iik(ij)} = \alpha_i + \sum_{l=1}^{L} \beta_l\, X_{ijkl}. \quad (27)$$

In this case, the relative salience of origin and destination statuses is allowed to depend on origin status, and the intercepts of the diagonal regression functions are allowed to vary, but the effects of the explanatory variables in these regression functions do not vary over origin (destination) statuses. This case, then, is analogous to the general model in the same way that analysis of covariance is analogous to the more general case in which there is an interaction effect between treatments and covariates.

Similarly case 2) may be obtained from (21)–(24) by rewriting $\mu_{iik(ij)}$ of equation (22) as:

$$\mu_{iik(ij)} = \alpha_i. \quad (28)$$

Note that case 2) is identical to the diagonal ANOVA model given by equations (7)–(10), and case 2) is a special instance of case 1).

[6] In equation (26), for reasons of simplicity, the mobility variables are contrasts between the diagonal and off diagonal cells of the mobility table. In general, one could also consider mobility variables that are interactions between these contrasts and various covariates.

Case 3) is also a special instance of case 1) and it is obtained by imposing the restriction in equation (27) (which defines case 1) and the additional restrictions $p_i = p, i=1,\ldots,R$, $r_i = r, i=1,\ldots,R$. Case 3) is the special instance of case 1) where the relative saliency of origins and destinations does not depend upon origin status. Except for this difference, the models for these two cases admit similar interpretations. It is also worth noting that case 3) is not a special instance of case 2), nor is case 2) a special instance of case 3).

Case 4) is obtained by imposing the restriction in equation (28) and the restrictions $p_i = p$, $i=1,\ldots,R, r_i = r, i=1,\ldots,R$. As such, this case, which is equivalent to the simple diagonal ANOVA model of equations (3)–(6), is a special instance of both cases 2) and 3).

Finally, from a statistical standpoint, cases 5) and 6) are identical. To see this, note that case 5) is obtained from (21)–(24) by rewriting $\mu_{iik(ij)}$ of equation (22) as:

$$\mu_{iik(ij)} = \alpha + \sum_{l=1}^{L} \beta_l X_{ijkl} \qquad (29)$$

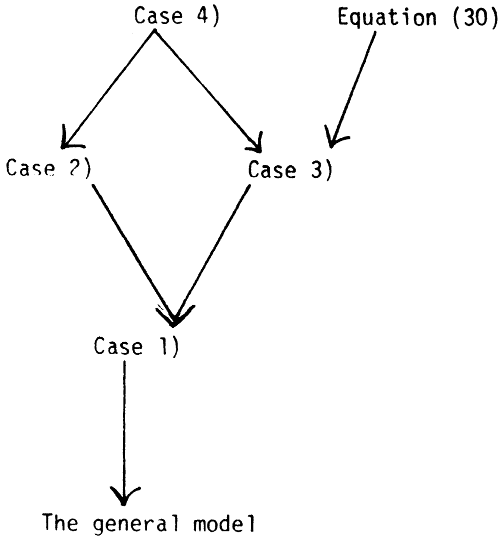
and case 6) is obtained by imposing the further restriction that $p_i = p, i=1,\ldots,R, r_i = r, i=1,\ldots,R$. In either case equation (25) reduces to:

$$y_{ijk} = \alpha + \sum_{l=1}^{L} \beta_l X_{ijkl} + \epsilon_{ijk}.\text{[7]} \qquad (30)$$

Model (30) is a linear regression model, and this model may be viewed as a special instance of cases 1) and 3).

Figure 1 displays the logical relations among cases 1)–4), the general model of equations (21)–(24) and the model of equation (30), using a Goodman (1973) type diagram.

Figure 1. The Relationship Between the General Model, Cases 1)–4), and the Model of Equation (30).



ESTIMATION AND HYPOTHESIS TESTING FOR DIAGONAL MODELS

In this section, estimation and hypothesis testing is briefly discussed for the diagonal models considered. Because the primary intent of this paper is not statistical, the discussion is not technical: readers who desire a more technical presentation of this type of material should consult Sobel (1981) and the references cited therein. In particular, a similar setup is discussed in Malinvaud (1966:360–64).

Sobel (1981) shows that if the ϵ_{ijk} are independently and identically normally distributed random variables with mean 0 and variance σ^2, maximum likelihood estimators of the parameters of the models (3)–(6), (7)–(10), and (11)–(14), and their analogues with mobility effects are identical to estimators obtained by non-linear least squares. In addition, if the inequality constraints given by equations (6), (10), and (14) are ignored, and if, under a particular model, the maximum likelihood estimates of the weight parameters lie in the closed unit interval, the estimators will be, under general regularity conditions (Theil, 1971; Rao, 1973), consistent and asymptotically normal with minimum asymptotic variance. For this reason, and because his estimates of the weights lie in the unit interval, Sobel suggests that in practice it is acceptable to ignore the inequality constraints. In this paper, following Sobel (1981), inequality constraints are not directly imposed on the weight parameters. While this may appear to have some disadvantages (if the unconstrained maximum likelihood estimators do not satisfy the inequality constraints), this method of proceeding also has a major advantage: if the weight coefficients do not suggest, under the model, that the weight parameters lie in the closed unit interval, this can be interpreted as evidence that the model is misspecified. Similarly, if the evidence from two otherwise comparable models suggests that a parameter p_i is not equal to a

[7] I might just as easily have framed this discussion in terms of a generalized version of the model given by equations (11)–(14). Had I done so, developing special cases 1′,. . ., 6′, I would find that cases 1 and 1′, and 2 and 2′ are not identical, but the other cases are.

parameter $1-p_j$ when i=j, this suggests the presence of specification error.[8]

To compare any two nested models (e.g., a model with and without mobility effects or the model (3)–(6) with the model (7)–(10)), a standard likelihood ratio test may be utilized. For such a comparison, one first computes the likelihood ratio $\lambda = (\hat{\sigma}_G/\hat{\sigma}_N)^n$, where $\hat{\sigma}_G$ is the maximum likelihood estimate of σ in the more general model, $\hat{\sigma}_N$ is the maximum likelihood estimate of σ in the nested model, and n is sample size (Goldfeld and Quandt, 1972:74). Next, the fact that $-2 \log \lambda$ has an asymptotic χ^2_r distribution, where r is the number of additional linearly independent parameters in the general model, is used to compare the two models.[9]

The procedures suggested by Sobel (1981) generalize immediately to the cases considered in this paper, except for cases 5) and 6) of the previous section. In these cases, the parameters of the function $\mu_{iik(ij)}$ in no way depend on origin or destination status. Consequently, in this instance, equation (25) reduces to equation (30). From (30) it is apparent that the model underlying the response variable is linear in the parameters; thus, for these two cases, the non-linear model reduces to the linear model, and ordinary least squares procedures can be used to estimate and test hypotheses about the parameters of the model, either with or without mobility effects. Note, however, that in case 5) the p_i and r_i parameters, $i=1,\ldots,R$, are not identified, and in case 6) the p and r parameters are not identified. Statistically, cases 5) and 6) cannot be distinguished from one another for these reasons.

Before turning to the example, there is one practical point about estimation that requires consideration. In the general versions of the diagonal model, it can be extremely expensive and/or practically prohibitive to iterate to a maximum likelihood solution, particularly when the sample size is large and the number of parameters requiring estimation is large, or even moderately large.

It is helpful, therefore, to start with initial parameter estimates that are consistent. These mays then serve as start values for the iterative maximum likelihood procedure. Alternatively, it is well known (Zacks, 1971; Amemiya, 1981; Berndt et al., 1974) that when consistent estimates are used as start values, the estimates obtained after only one Newton–Raphson iteration are asymptotically equivalent to maximum likelihood estimates, and therefore have the same large sample properties as the maximum likelihood estimators. In large samples, with numerous parameters to estimate, the use of this latter strategy can lead to enormous savings.[10, 11] Appendix A describes an algorithm that can be used to obtain consistent estimates of the model parameters.

SOCIAL MOBILITY AND FERTILITY REVISITED

To illustrate these models, the relationship between intergenerational occupational mobility (father's occupation to son's occupation in March, 1962) and fertility (number of children ever born) is reconsidered, using data from the OCG–I study (Blau and Duncan, 1967).

Following Blau and Duncan (1967), the population is defined as wives, aged 42 to 61 as of March, 1962, currently living with OCG spouses. The occupational categories of the husband by which the observations are crossclassified are:

1. higher white-collar workers
2. lower white-collar workers
3. higher manual workers
4. lower manual workers
5. farmers.

The independent variables used in the analysis are:

1. EDCPX—husband's education, measured in years of completed schooling;
2. EDCPW—wife's education, measured in years of completed schooling;
3. EDED—the product of EDCPX and EDCPW;
4. FRMORW—farm origins of wife, scored 1 if yes, 0 otherwise;

[8] Alteratively, if a weight coefficient lies outside the unit interval, one could fix the value of that weight to the nearest boundary value and re-estimate the model. See Barlow et al., 1972, for further discussion.

[9] We do not consider comparisons between non-nested models in this paper.

[10] For example, starting with consistent estimates, it cost about $1000 (at this institution) to produce maximum likelihood estimates of the parameters of model 14 in the example section; under the alternative strategy, the cost was about $50.

[11] These models can also be viewed as covariance structure models with nonstochastic latent variables $\mu_{iik(ij)}$ and $\mu_{jjk(ij)}$ and weight parameters that are subject to both linear and non-linear restrictions. Presumably, a program such as COSAN (McDonald, 1980) could be used to estimate the parameters of the models considered in this paper. This approach was not pursued because a) COSAN is a very specialized program that is not currently workable at this or many other institutions, and b) the approach I take is likely to be substantially cheaper.

Table 1. Social Mobility and Fertility—Model Descriptions

Model Number	Weights	Intercept	Regression Parameters	Mobility Effects	Number of Linearly Independent Parameters	$\hat{\sigma}^2$
1	p or p_i or p_j	α	β_l	No	10	3.3342
2	p or p_i or p_j	α	β_l	Yes	13	3.3312
3	p	α_i	β_l	No	15	1.9979
4	p	α_i	β_l	Yes	18	1.9931
5	p	α_i	β_{il}	No	51	1.9430
6	p	α_i	β_{il}	Yes	54	1.9394
7	p_j	α_i	β_l	No	19	1.9922
8	p_j	α_i	β_l	Yes	22	1.9883
9	p_j	α_i	β_{il}	No	55	1.9595
10	p_j	α_i	β_{il}	Yes	58	1.9528
11	p_i	α_i	β_l	No	19	1.9885
12	p_i	α_i	β_l	Yes	22	1.9837
13	p_i	α_i	β_{il}	No	55	1.9316
14	p_i	α_i	β_{il}	Yes	58	1.9288

5. SCTYPX—a proxy for Catholicism, scored 1 if the husband attended a parochial school, 0 otherwise;
6. AGEMW—wife's age at marriage;
7. SIBX—number of siblings in husband's family of orientation;
8. SIBW—number of siblings in wife's family of orientation;
9. SIBSIB—the product of SIBX and SIBW;
10. MOB—a mobility contrast, scored 1 if husband is mobile, 0 otherwise;
11. DIR—direction of mobility, scored 1 if upward, −1 if downward, 0 otherwise.
12. STEPS—number of status changes upward or downward, as given by origin rank minus destination rank.

Variables 1–9 are chosen on theoretical grounds, and a similar list of explanatory variables is suggested by Duncan (1965) and Duncan et al (1965). The mobility variables are those suggested by preliminary analyses of the data.[12]

After excluding observations with missing data on one or more of the variables of interest, 5155 cases were obtained. All these cases were used to obtain consistent estimates of the parameters of models 3–14 (see Table 1). These estimates then served as start values for the iterative routine. In employing the iterative routine (a user-defined procedure within a BMDP nonlinear regression routine), computational limitations necessitated the use of a sample size closer to 2000; a simple random sample of 1970 of the 5155 observations was drawn. Next, one iteration (see the previous section) was carried out, yielding estimates that are asymptotically equivalent to maximum likelihood estimates.

Table 1 presents the 14 models considered in this paper. The first four columns of this table suffice to describe each model. Column 1 indicates that the weights are either constant across origin (destination) categories (p), or variable across origins (p_i), or variable across destinations (p_j). Similarly, column 2 indicates that the intercepts of the regression function are either constant across origins and destinations (α), or variable across origins and destinations (α_i), while column 3 indicates that the other parameters of the regression function are either constant across origins and destinations (β_l), or variable across origins and destinations (β_{il}). Finally, column 4 indicates whether or not the three mobility variables are included in the analysis.[13]

Column 5 reports the number of linearly independent parameters estimated under each model and column 6 reports the estimated error variance of each model. The information in these columns, coupled with a knowledge of the sample size, is sufficient for formulating

[12] Analyses that either do not include mobility effects, or only include the effect of the variable MOB do not assume that the occupational categories are ordered. Analyses that include the effect of the variable DIR do assume the existence of a rank order, and analyses that include the effect of STEPS assume that this effect is linear. However, analyses that include the effect of STEPS do not necessarily imply that the occupational categories are equally spaced on a socioeconomic or prestige dimension.

[13] Notice that diagonal ANOVA models, as given by equations (3)–(6), (2)–(10), and (11)–(14), as well as their analogues with mobility effects, are not explicitly examined here, as the intent of this work is to illustrate the extensions of these models. Furthermore, at the .05 level of significance, the diagonal ANOVA models do not fit the data as well as the more general models.

comparisons between nested models by means of a likelihood ratio test, as described in the previous section.[14] Figure 2, which displays the logical relations between the 14 models, indicates how these models are nested.

The choice of a preferred model for these data is, at least in the abstract, an exceedingly complex issue, because there are four dimensions (as indicated by the first four columns of Table 1) along which any such choice hinges. In practice it must be decided whether or not the preferred model includes or does not include mobility effects, incorporates one or more than one weight parameter, and so on. Model comparisons can focus on one or more dimensions in a given comparison, and even comparative strategies that focus on one dimension at a time can yield ambiguous and conflicting results. For example, the even numbered models in Table 1 incorporate mobility effects, and the odd numbered models do not; this yields seven potential likelihood ratio tests for the presence of mobility effects, and these tests need not all point to the same conclusion. It is necessary as well to ascertain whether or not other model parameters are allowed to vary across origins and/or destinations; the magnitude of the comparative problem increases sharply.

Despite this potential complexity, the results are unequivocal. Table 2 reports likelihood ratio comparisons that lead to the choice of model 13 as the preferred model for these data.

Panel A of Table 2 compares nested models with and without mobility effects. These seven comparisons strongly indicate that a preferred model can be chosen from the seven models that do not incorporate mobility effects, rejecting the hypothesis that mobility effects exist. We need to focus attention, therefore, only on the seven models that do not incorporate mobility effects.

The simple non-linear model 3 is then compared with the linear model 1 (panel B); the χ^2 value in excess of 1000 indicates that any of the non-linear models under consideration are far superior to model 1. This leaves models 3, 5, 7, 9, 11, and 13 for further consideration.

In panel C models 3, 7, and 9 are compared. From Table 1, it is apparent that models 9 and 3 differ in two respects. First, in model 9, the weight parameters are not invariant with respect to destinations, as in model 3. Second, in model 9, the regression parameters are allowed to vary across origins and destinations. The test between models 9 and 3 (first entry of panel C) indicates that model 9 is not statistically superior to model 3, as the χ^2 value corresponds to a probability level in excess of .5. Furthermore, because the likelihood ratio χ^2 is additive and 36 degrees of freedom are used to allow the regression parameters to vary across origins and destinations, it is not possible, given the χ^2 value of 38.33 obtained, that model 5 be preferred to model 3, or model 9 to model 7. However, it is still possible that an intermediate model which allows the weight parameters to vary across origins is preferable to model 3. This suggests a comparison between models 3 and 7. From this comparison (second

Figure 2. The Relationship Between the 14 Models in Table 1.

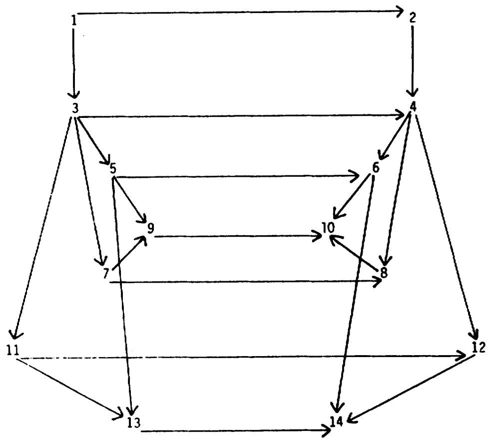


Table 2. Social Mobility and Fertility—Selected Model Comparisons

Comparison	Degrees of Freedom	Likelihood Ratios chi-square
A.		
1–2	3	1.80
3–4	3	4.75
5–6	3	3.69
7–8	3	3.82
9–10	3	6.72
11–12	3	4.79
13–14	3	2.82
B.		
1–3	5	1008.88
C.		
3–9	40	38.33
3–7		5.72
D.		
3–13	40	66.54
5–13	4	11.63
11–13	36	57.20

[14] Notice that the error variances for models 9 and 10 exceed the error variances for models 5 and 6, respectively, despite the fact that the latter models are nested under the former. This apparent anomaly is due entirely to the fact that the estimates produced here (based on one iteration) are only asymptotically equivalent to maximum likelihood estimates. Despite this anomaly, the testing procedures used here are justifiable (Amemiya, 1981).

line of panel C), it is obvious that model 3 is preferred among models 3, 5, 7, and 9.

In panel D, a similar exercise is repeated, comparing models 3, 5, 11, and 13; note that it is already known that model 5 is not superior to model 3. The first line of panel D compares models 3 and 13. The χ^2 value of 66.54 is significant at the .05 level. This does not suggest, in and of itself, that model 13 is the preferred model, for it may not be superior to one or both of the nested models 5 and 11. The entries on the second and third lines of panel D address this issue. In both cases, model 13 is superior, and this suggests that model 13 is the preferred model for these data.[15]

In model 13, the weights are allowed to vary across origins, and the parameters of the regression function are allowed to vary across origins and destinations, i.e., the covariates are allowed to interact with origins and destinations. Note that model 13 is the general model, as given by equations (21)–(24).

Table 3 gives parameter estimates and standard errors for the coefficients of model 13. Despite the fact that there are no mobility effects, several features of the model are interesting. First, traditional models for the analysis of mobility effects do not permit conclusions about the relative salience of origins and destinations in the acculturation process, whereas the models considered here do allow for such inferences. We find then that origins and destinations are not equally salient, and learn that the relative salience of origin status to destination status depends on origin status. Though $\hat{p}_1$ and $\hat{p}_2$ are greater than 1 and less than 0, respectively, note that the 95 percent confidence intervals for p_1 and p_2 cover the values 1 and 0 respectively.[16] Descriptively, the results suggest that p_1 is at least .75, that p_1 exceeds p_2, p_3, p_4, and p_5, that p_3, p_4, and p_5 are roughly comparable in magnitude, and that p_2 is less than p_3, p_4, and p_5, as well as p_1. The model suggests that acculturation to the norms of the origin status group is strong for higher white-collar workers, moderate for manual workers and farmers, and weak for lower white-collar workers. With respect to fertility, at least, hypotheses that argue for the unimportance of socialization to destination norms can be rejected. These findings are considered at greater length in the concluding section.

Turning now to the effects of the independent variables, we find that these effects vary by origin (destination) status. That is, the effects of the explanatory variables are conditioned by differential location in the stratification system. This suggests that simple models of social processes which a priori impose identical effects at all levels of the stratification system are misleading, at least in this context, and perhaps more generally.

Specifically, wife's age at marriage is significantly (at the .05 level) and inversely related to fertility levels in all but status category 2; in this category, the negative effect is almost significant at the .05 level. Second, the proxy for Catholicism (SCTYPX) is significant, at the .05 level, for higher manual workers, and it is almost significant for higher white-collar workers. In both cases, Catholicism serves to augment fertility, as one might expect. But, among lower white-collar workers, lower manual workers, and farmers, the effect of Catholicism on fertility appears to be nil. Third, the effects of the sibling variables are significant or almost significant, at the .05 level, only among higher manual workers (β_{37} and β_{38}) and farmers (β_{59}). The effect of additional siblings here is to augment fertility. However, among white-collar workers and lower manual workers, no effect of the sibling variables on fertility is found. Fourth, the effects of the education variables are significant, at the .05 level, only among higher white-collar workers; in this category, increments to education yield decreased fertility. Among lower white-collar workers, the education variables operate in the same fashion, but these effects are not quite significant at the .05 level. There are no significant education effects for manual workers or farmers. Finally, the effects of the variable FRMORW are never significant; all else equal, wife's farm background does not affect fertility.

SUMMARY AND CONCLUSIONS

This paper develops new models for the investigation of the mobility effects hypothesis and reexamines the relationship between social mobility and fertility, as previously considered by Blau and Duncan (1967). The portion of the analysis that pertains to mobility appears to confirm the major conclusions reached by Blau and Duncan (1967:397): "By and large the fertility of mobile couples, which is intermediate between that prevailing in their origin and that prevailing in their destination stratum, can

[15] Note that if model 13 were not superior to model 5, which is in turn not superior to model 3, it could still be the case that model 13 is superior to model 3. Similarly, model 13 can be superior to both models 3 and 11, without model 11 being superior to model 3. In fact, for these data, model 11 is not superior to model 3.

[16] The notation could be modified to indicate that $p_1, \ldots, p_5$ correspond to the parameters p_i, $i=1, \ldots R$, and not p_j, $j = 1, \ldots R$. However, since the p_j, $j = 1, \ldots, R$ are not considered further, the additional notational complexity is not warranted.

Table 3. Social Mobility and Fertility—Model 13 Parameter Estimates and Asymptotic Standard Errors

Variable or Parameter Description	Status Category	Parameter	Parameter Estimate	Asymptotic Standard Error
Weight	1	p_1	1.1556	.2073
Weight	2	p_2	−.1336	.2178
Weight	3	p_3	.4616	.1318
Weight	4	p_4	.6016	.1584
Weight	5	p_5	.4960	.1084
Intercept	1	α_1	5.9734	1.3059
EDCPX	1	β_{11}	−.2756	.1067
EDCPW	1	β_{12}	−.3013	.1099
(EDCPX)(EDCPW)	1	β_{13}	.0226	.0087
FRMORW	1	β_{14}	.0786	.1995
SCTYPX	1	β_{15}	.4871	.2651
AGEMW	1	β_{16}	−.0583	.0148
SIBX	1	β_{17}	.0047	.0567
SIBW	1	β_{18}	−.0479	.0566
(SIBX)(SIBW)	1	β_{19}	.0160	.0127
Intercept	2	α_2	−.1731	4.8350
EDCPX	2	β_{21}	.1753	.4358
EDCPW	2	β_{22}	.0281	.4138
(EDCPX)(EDCPW)	2	β_{23}	−.0075	.0372
FRMORW	2	β_{24}	−.0023	.5786
SCTYPX	2	β_{25}	−.2203	.5955
AGEMW	2	β_{26}	−.0687	.0482
SIBX	2	β_{27}	.1927	.1990
SIBW	2	β_{28}	.3547	.1849
(SIBX)(SIBW)	2	β_{29}	−.0635	.0427
Intercept	3	α_3	.0098	1.9450
EDCPX	3	β_{31}	.0653	.1884
EDCPW	3	β_{32}	.2396	.1746
(EDCPX)(EDCPW)	3	β_{33}	−.0041	.0165
FRMORW	3	β_{34}	−.1372	.2794
SCTYPX	3	β_{35}	.6751	.3238
AGEMW	3	β_{36}	−.1479	.0238
SIBX	3	β_{37}	.1631	.0837
SIBW	3	β_{38}	.2047	.0919
(SIBX)(SIBW)	3	β_{39}	−.0251	.0171
Intercept	4	α_4	4.5169	1.0796
EDCPX	4	β_{41}	−.1520	.1110
EDCPW	4	β_{42}	−.1804	.1039
(EDCPX)(EDCPW)	4	β_{43}	.0156	.0104
FRMORW	4	β_{44}	−.2324	.2328
SCTYPX	4	β_{45}	−.2921	.2502
AGEMW	4	β_{46}	−.0770	.0193
SIBX	4	β_{47}	−.0217	.0676
SIBW	4	β_{48}	.0503	.0781
(SIBX)(SIBW)	4	β_{49}	.0076	.0132
Intercept	5	α_5	2.8757	1.0748
EDCPX	5	β_{51}	−.0299	.1155
EDCPW	5	β_{52}	−.0624	.0900
(EDCPX)(EDCPW)	5	β_{53}	.0021	.0101
FRMORW	5	β_{54}	.3469	.2414
SCTYPX	5	β_{55}	.4738	.3838
AGEMW	5	β_{56}	−.1345	.0258
SIBX	5	β_{57}	.1424	.0887
SIBW	5	β_{58}	.0837	.0899
(SIBX)(SIBW)	5	β_{59}	.1257	.0155

be explained by the additive influence of these two social strata." However, the new analysis does not lend credibility to the claim (Blau and Duncan, 1967:397) that long distance mobility depresses fertility.

Although the new results largely confirm those on mobility effects reached by Blau and Duncan, this is not an indication that the models proposed here merely offer a more sophisticated way to reach familiar conclusions. Four reasons explain this. First, the similarity between these results and those obtained by Blau and Duncan is an isolated empirical fact, and not a general regularity. Second, our results contradict some of the results obtained by Blau and Duncan. Third, our models are conceptually suited to the task at hand, whereas the square and diamond–additive models are not; thus the diagonal models are always preferable to these alternatives.[17] Finally, whether or not mobility effects are present, the diagonal models with covariates allow researchers to both examine the impact of suitably chosen explanatory variables on the phenomenon under investigation and to assess the relative salience of (various) origin and destination states to the acculturation process. By permitting inferences that were previously unobtainable, these new models pave the way for generating new questions and expanding the theoretical agenda. Instead of focusing narrowly on the mobility effect hypothesis, as in the past, future workers may find it profitable to construct and test more elaborate sociological propositions about the relative and/or differential importance of origins and destinations.[18]

For example, one might hypothesize that socialization to origin norms operates weakly when mobility out of that state is prevalent and/or anticipated, and strongly when this is not the case. All else equal, the prevalence hypothesis suggests that the origin weights (see, for example, models 10–14 in Table 1) should vary directly with the conditional probability of remaining in the class of origin (hereafter $p_{i|i}^{*}$) and that when these conditional probabilities are equal across origin classes, the weights should be invariant across origin classes, as in models 3–6 of Table 1.

Table 4 (Sobel, 1981) sheds light on the prevalence hypothesis.[19] From the frequencies in the table, the estimated conditional probabilities of remaining in origin classes 1,. . .,5, are, respectively: .56, .16, .28, .37, and .22. If the prevalence hypothesis is correct, then, all else equal, $p_1 > p_4, > p_3, > p_5 > p_2$. The previous results (Table 3) descriptively suggest that p_1 is largest, followed by p_3, p_4, and p_5, which are comparable in magnitude, and p_2. As such, some descriptive, but not overwhelming, support is offered for the hypothesis itself.[20]

Table 4. Cross-classification of Husband's Father's Occupation and Husband's March, 1962 Occupation, for Wives 42 to 61 Years Old in March, 1962, Living with Husband, in OCG Sample

Husband's Father's Occupational Category	Husband's 1962 Occupational Category: 1	2	3	4	5
1	538	137	129	130	20
2	190	65	54	71	10
3	318	153	307	269	20
4	322	163	345	513	34
5	389	148	462	687	484

Note: n = 5958.

The prevalence and anticipation hypotheses in turn suggest further elaborations on our models. Specifically, the prevalence hypothesis suggests that p_i, i=1, . . .,R, is a function of the conditional probabilities $p_{i|i}^{*}$, i=1, . . ., R, and perhaps, other factors. The anticipation hypothesis suggests that different individuals have different expectations about mobility, and these expectations may be a function of various exogenous variables. As such, the p_i, i=1, . . .,R (which are fixed effects in the diagonal models proposed here) might be replaced by individual specific random effects that may depend on a vector of exogenous variables and a parameter set Ω.[21]

Other developments are also possible, though not all of these are discussed here. The extension from a two-way cross-classification to a multi-way cross-classification is not discussed. These and other developments may constitute a potentially rich ground for future workers interested in a variety of substantive topics. While the focus here is on the mobility problem, diagonal models can be fruitfully applied in other areas, e.g., the study of socialization processes. These models (or models like these) could be used to study further examples outside the mobility area, such as:

a) the relationship between geographic mobility and income (Featherman and Hauser, 1978);
b) religious conversion and fertility (Janssen and Hauser, 1980);
c) household decisions that are contingent on the educational homogamy of marital partners (Bumpass and Sweet, 1972);
d) the effects of status inconsistency.

[17] This does not suggest, however, that the diagonal models unequivocally apply in all mobility effects research. See Sobel (1981:904) for further discussion of this point.

[18] Curiously enough, this issue, which is at least as important and interesting as the mobility effects hypothesis, has been largely ignored.

[19] The sample size for Table 4 is 5958, rather than 5155, because 803 of the 5958 cases in Table 4 had data missing on one or more of the independent variables used in the analysis herein.

[20] I do not attempt to rigorously assess the prevalence hypothesis in this paper because a) the hypothesis itself is suggested by a post-hoc analysis of the results, and b) such a task, which would require separating the influence of anticipations and prevalence, is well beyond the scope of this paper.

[21] Gerhard Arminger and I are currently working together on these and other extensions.

APPENDIX A. Obtaining Consistent Estimates for Use as Start Values

To obtain consistent estimates of the parameters of our models the following simple procedure may be used:

Step 1. Take the diagonal responses only and use ordinary least squares to estimate $\mu_{iik(ii)}$ of equation (18), $i=1,\ldots,R$. Under general conditions (Theil, 1971) this procedure yields consistent estimates of the parameters of (18).[22]

Step 2. Use the consistent estimates obtained in step 1 to construct estimates of the $\mu_{iik(ij)}$ and $\mu_{jjk(ij)}$ of equations (19) and (20) for all observations. These estimates will also be consistent under general conditions.

Step 3. Under the model of interest, impose the linear restrictions (e.g., $r_i = 1-p_i$, $i=1,\ldots,R$) to algebraically transform the equation for y_{ijk} and then use ordinary least squares to obtain consistent estimates of the weight parameters and, if included, the mobility effects. Then, if one or more of the resulting weight coefficients lies outside the unit interval, it should be set at the value of the closest endpoint.

For example, suppose the model under consideration is given by (21)–(24). In step 1, take observations on the diagonal, partition these into the appropriate groups, $i=1,\ldots,R$, and estimate the R regression equations. Note that this requires at least L+1 observations for each diagonal cell. Next, use the parameter estimates to construct estimates $\hat{\mu}_{iik(ij)}$ and $\hat{\mu}_{jjk(ij)}$ of $\mu_{iik(ij)}$ and $\mu_{jjk(ij)}$ for all observations in the sample. Next, using (23), transform equation (25) to:

$$y_{ijk} - \hat{\mu}_{jjk(ij)} = p_i(\hat{\mu}_{iik(ij)} - \hat{\mu}_{jjk(ij)}) + \epsilon^*_{ijk},$$

and use ordinary least squares to estimate the parameters p_i, $i=1,\ldots,R$. If a parameter estimate, say $\hat{p}_1$, lies outside of [0,1], define a new estimate $\hat{\hat{p}}_1 = 0$ if $\hat{p}_1 < 0$ and $\hat{\hat{p}}_1 = 1$ if $\hat{p}_1 > 1$. Otherwise, $\hat{\hat{p}}_1 = \hat{p}_1$.

The procedure above yields consistent estimates of all the parameters of the model, with the exception of the parameter σ^2. In general, a consistent estimate of σ^2 is not needed; however, if a consistent estimate of σ^2 is needed, such an estimate may be obtained as SSR/n, where SSR is the residual sum of squares obtained by using the consistent estimates of the other parameters to define fitted values $\hat{y}_{ijk}$, i.e., $SSR = \sum_{i,j,k} (y_{ijk} - \hat{y}_{ijk})^2$, and n is the total sample size.

[22] Equation (18) is the most general specification of $\mu_{iik(ii)}$ considered here. The procedure also works for the less general functions subsequently considered.

REFERENCES

Amemiya, Takeshi
1981 "Qualitative response models: a survey." Journal of Economic Literature 19:1483–1536.

Barlow, R., D. Bartholomew, J. M. Bremner, and H. D. Brunk
1972 Statistical Inference Under Order Restrictions. New York: Wiley.

Berndt, E. K., B. H. Hall, R. E. Hall, and J. A. Hausman
1974 "Estimation and inference in nonlinear structural models." Annals of Economic and Social Measurement 3:653–65.

Berent, Jerzy
1952 "Fertility and social mobility." Population Studies 5:244–60.

Blau, Peter M.
1956 "Social mobility and interpersonal relations." American Sociological Review 21:290–95.

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

Bumpass, Larry J. and James A. Sweet
1972 "Differentials in marital instability: 1970." American Sociological Review 37:754–66.

Curtis, Richard F. and Elton F. Jackson
1977 Inequality in American Communities. New York: Academic.

Dumont, Arsène
1890 Dépopulation et Civilisation. Paris.

Duncan, Otis D.
1965 "Farm background and differential fertility." Demography 2:240–49.
1966 "Methodological issues in the analysis of social mobility." Pp. 51–97 in Nell J. Smelser and Seymour M. Lipset (ed.), Social Structure and Mobility in Economic Development. Chicago: Aldine.

Duncan, Otis, D., Ronald Freedman, J. Michael Coble and Doris P. Slesinger
1965 "Marital fertility and size of family of orientation." Demography 2:508–15.

Easterlin, Richard A.
1975 "An economic framework for fertility analysis." Studies in Family Planning 6:54–63.

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

Freedman, Deborah
1953 "The relation of economic status to fertility." American Economic Review 53:414–26.

Goldfeld, Stephen M. and Richard E. Quandt
1972 Nonlinear Methods in Econometrics. Amsterdam: North-Holland.

Goldthorpe, John H.
1980 Social Mobility and Class Structure in Modern Britain. Oxford: Clarendon Press.

Goodman, Leo A.
1972 "Some multiplicative models for the analysis of cross-classified data." Pp. 646–96 in L. Le Cam, J. Meyman, and E. L. Scott (eds.), Proceedings of the Sixth Berkeley Symposium on Mathematical Statistics and Probability. Berkeley: University of California Press.
1973 "Guided and unguided methods for the selection of models for a set of T multidimensional contingency tables." Journal of the American Statistical Association 68:165–75.

Halaby, Charles N. and Michael E. Sobel
1979 "Mobility effects in the workplace." American Journal of Sociology 85:385–416.

Hope, Keith
1975 "Models of status inconsistency and social mobility effects." American Sociological Review 40:322–43.

Jackman, Mary R.
1972 "The political orientation of the socially mobile in Italy: a re-examination." American Sociological Review 37:213–22.

Jackson, Elton F. and Richard F. Curtis
1972 "Effects of vertical mobility and status inconsistency: a body of negative evidence." American Sociological Review 37:701–13.

Janssen, Susan G. and Richard M. Hauser
1980 "Religion, socialization, and fertility." Center for Demography and Ecology Working Paper 80–5. Madison: University of Wisconsin.

Kessin, Kenneth
1971 "Social and psychological consequences of intergenerational occupational mobility." American Journal of Sociology 77:1–18.

Knoke, David
1973 "Intergenerational occupational mobility and the political party preferences of American men." American Journal of Sociology 78:1148–68.

Kohn, Melvin L.
1977 Class and Conformity: A Study of Values. Second edition. Chicago: University of Chicago Press.

Langner, Thomas S. and Stanley T. Michael
1963 Life Stress and Mental Health. New York: Free Press.

Laslett, Barbara
1971 "Mobility and work satisfaction: a discussion of the use and interpretation of mobility models." American Journal of Sociology 77:19–35.

Levinson, Daniel J., C. N. Darrow, E. B. Klein, M. H. Levinson and B. McKee
1978 The Seasons of a Man's Life. New York: Ballantine.

Lewis, Oscar
1966 "The culture of poverty." Scientific American 16:19–25.

Liem, Ramsey and Joan Liem
1978 "Social class and mental illness reconsidered: the role of the economic stress and social support." Journal of Health and Social Behavior 19:139–56.

Malinvaud, Edmond
1966 Statistical Methods of Econometrics. Amsterdam: North-Holland.

McDonald, Roderick P.
1980 "A simple comprehensive model for the analysis of covariance structures: some remarks on application." British Journal of Mathematical and Statistical Psychology 33:161–83.

Rao, Calyampudi R.
1973 Linear Statistical Inference and its Applications. New York: Wiley.

Riemer, Ruth and Clyde V. Kiser
1954 "Economic tension and social mobility in relation to fertility planning and size of planned family." Milbank Memorial Fund Quarterly 32:167–231.

Seeman, Melvin
1977 "Some real and imaginary consequences of social mobility: a French-American comparison." American Journal of Sociology 82:757–82.

Sobel, Michael E.
1981 "Diagonal mobility models: a substantively motivated class of designs for the analysis of mobility effects." American Sociological Review 46:893–906.

Sorokin, Pitrim A.
1927 Social and Cultural Mobility. New York: Free Press.

Stone, Robert C.
1952 "Mobility factors as they affect workers' attitudes and conduct toward incentive systems." American Sociological Review 17:58–64.

Theil, Henri
1971 Principles of Econometrics. New York: Wiley.

Tien, H. Yuan
1961 "The social mobility/fertility hypothesis reconsidered: an empirical study." American Sociological Review 26:247–57.

Westoff, Charles F.
1953 "The changing focus of differential fertility research: the social mobility hypothesis." Milbank Memorial Fund Quarterly 31:24–38.

Wilensky, Harold L.
1966 "Measures and effects of social mobility." Pp. 98–140 in N. J. Smelser and S. M. Lipset (eds.), Social Structure and Mobility in Economic Development. Chicago: Aldine.

Winer, B. J.
1972 Statistical Principles in Experimental Design. New York: McGraw-Hill.

Zacks, Shelemyahu
1971 The Theory of Statistical Inference. New York: Wiley.