MULTISTATE DEMOGRAPHY AND EVENT HISTORY ANALYSIS

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FOREWORD

The ways in which our society may have to adapt and respond to changes induced by energy shortages, environmental ceilings, and food insufficiencies has been the subject of much analysis and debate during the past decade. In all of this flurry of concern with perceived limits to growth, however, insufficient attention has been accorded to the effects of a variable that may overshadow all of the rest in importance: changing population dynamics and lifestyles and their socioeconomic impacts.

Explosive population growth in the less developed countries and population stabilization in the more developed nations have created unprecedented social issues and problems. The future societal ramifications of changing age compositions, patterns of family formation and dissolution, movements from one region to another, health status and demands for care, and participation in the labor force will be profound.

Rapid social change combined with heterogeneity in populations in skills and experiences leads to disparities in well-being (e.g., income and health) among various subgroups of national populations: between generations, between social groups, and between rural/urban sectors. All too often policies designed to redress such disparities stand a good chance of worsening them unless consideration is given to the full range of indirect effects of the policies.

In this paper, Michael Hannan explores a merger of two methodologies for the purpose of analyzing the direct and indirect long-run implications of behavioral responses to public policies: multistate demography and life history or event history analysis. He argues that such a combined approach allows one to project levels of well-being in heterogeneous populations facing changing social policies.

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1. INTRODUCTION

Numerous social sciences and public policy problems concern the movement of a population over a set of discrete states. For example, demographers and population planners typically project the movement of national populations among regions over long time spans. Labor economists analyze effects of public policies on movement between employment and nonemployment. Sociologists study movement over sets of occupational or status classes. A strong convergence of interests by policy makers and social scientists in the dynamics of movements of populations over qualitative states can be seen clearly in the social experiments conducted in the U.S. during the 1970s. For example, the largest such experiment, the Seattle-Denver Income Maintenance Experiment, was designed to estimate the effects of income guarantees on changes in employment and marital statuses (Groeneveld et al., 1981).

Two quite different traditions for analyzing the movement of populations over discrete states have developed in the social sciences. One tradition uses demographic concepts and procedures;

*This paper draws heavily on joint work with Nancy Brandon Tuma. James Coleman and Andrei Rogers made helpful comments on an earlier draft.

the other tradition combines sociological methods and ideas from stochastic process analysis. Though there has been little flow of ideas between the two traditions, recent developments suggest that an attempt to merge them might be fruitful.

The demographic tradition revolves around the analysis of life tables and projections. It seeks mainly to answer questions about the long-run implications of a current set of rates. The life table method applies such rates to a hypothetical population stream, characterizing the events that would occur if future generations were exposed to the current structure (see Keyfitz, 1977 for a detailed discussion). Since life table models and methods were developed in the context of mortality studies, they pay attention to age-dependence of rates and to inferences about the expectation of lengths of lifetimes. However, this approach plays down the importance of heterogeneity within a population of the same age, preferring to investigate the implications of age-varying rates in a homogeneous population. When heterogeneity is recognized, demographers typically disaggregate the population and perform a separate analysis within each subpopulation.

The alternative approach, which developed primarily in sociology, combines behavioral hypotheses about the effects of heterogeneity on rates with stochastic process models. It tries to measure differences among individuals (in social class, for example) and to parameterize the effects of such heterogeneity on rates of moving between states. The sociological tradition has also emphasized the effects of duration in a state on rates of leaving the state (see, for example, McGinnis, 1968). It has also incorporated ideas developed by statisticians about the effects of unobserved heterogeneity, such as the famous mover-stayer model of Blumen et al. (1955)--see, for example, Coleman (1964) and Spilerman (1972b). However, the sociological tradition has given little attention to age-variation in rates and has tended to worry less about long-run projections, preferring to concentrate on the causal structure affecting current rates.

The power of the demographic approach was increased considerably when Rogers (1973, 1975) extended the life table model to handle *repeatable* events such as migration. Assuming a stationary first-order Markov process, Rogers showed that all of the usual life table functions defined for the "decrement only" case could be generalized to the case where the life table changes both by "increments and "decrements."* Operational methods for estimating the parameters of such Markov processes in the context of migration and methods for projecting migration flows were developed by Rogers and his collaborators (see, for example, Willekens and Rogers, 1978). An extension to marital status changes was made by Schoen (1975) and Schoen and Land (1979).

The development of multistate life table methods brought the demographic tradition much closer to the sociological one. In particular, the centerpiece of Coleman's (1964) influential book on mathematical sociology was the application of stationary Markov processes to the problem of estimating the causal structure underlying repeatable events. Despite the formal similarity of these two modeling efforts, multistate demography has not profited from methodological developments in sociological analysis. Multistate demography continued the demographic tradition of emphasizing age-dependence in rates but glossing over other forms of heterogeneity within populations.

Why has there been so little connection between the two approaches? Perhaps, demographers are not very interested in population heterogeneity. The well-developed paradigm of life table analysis certainly does not direct interest in this direction. But, there are also a number of technical matters that have impeded the flow of ideas from one field to another. One apparent obstacle involves the parameterization of time. Demographic analysis typically uses a discrete-time parameterization, where the time lag is determined by the spacing of observations; sociological analysis of qualitative dynamics has typically used a continuous-time specification. Moreover, terminology and notation differ greatly between the two styles of work. Perhaps a

*Keyfitz (1979) gives an overview and appreciation of the multistate demographic approach.

more important obstacle to incorporating causal arguments into demographic models was the lack of any satisfactory method of estimating parameterized causal effects. Coleman (1964, 1968) developed a method of estimating such effects from panel data. However, his method required the assumption that the distribution had reached a steady state, which is often substantially unrealistic. Moreover, Singer and Spilerman (1976) showed that a set of transition probabilities estimated from panel data cannot necessarily be embedded in a continuous-time Markov process for even a homogeneous population. The presence of heterogeneity exacerbates the problems of panel inference.

Substantial progress has been made in recent years in developing procedures for estimating causal models for rates. In large part, this progress depended upon shifting away from reliance on panel data to using the actual histories of events to individuals, the timing and sequence of events.* The models and methods developed for such detailed observation plans are often called *event history* or *sample path* methods. There has been progress on at least three fronts in social science analysis of event histories. First, sociologists have generalized standard hazard function methods for analyzing causal effects on rates for repeatable events (see Tuma, 1976; Sorensen, 1977; Tuma et al., 1979). Second, Cox's (1972, 1975) powerful non-parametric procedure for estimating causal effects in the presence of unknown time-varying noise functions has been applied in sociological research. Third, social scientists and statisticians have begun to attack the problem of estimating the effects of unobserved heterogeneity on rates (see Tuma, 1980; Heckman and Singer, in press), and of separating the effects of unobserved individual-specific heterogeneity from

*The use of event history methods in demography actually involves a double shift: from discrete-time to continuous-time models and from panel data to event history data. Coleman (1981a, 1981b) shows that there are substantial advantages in using continuous-time models even when only panel data are available. In the interest of stimulating demographers to exploit available event history data and to collect more of them, this paper concentrates on the "best" case--continuous-time models applied to event history data.

duration-dependence (Heckman and Borjas, 1980; Chamberlain, 1979). In general, the empirical analysis of event histories has become a topic of active research in sociology and economics, as well as in biometrics and reliability theory.

Because the newly developing models and methods for event-history analysis apply to repeatable events, they are applicable in a multistate demographic context, as has been noted by Land and Rogers (in press). Indeed, an infusion of event history methods into multistate demography would be highly desirable. It would combine the power of multistate demography for deriving long-run implications of current (perhaps fragmentary) rates with the realism and behavioral emphasis of event history analysis as practiced in sociology.

By allowing transition rates to vary with observed and unobserved heterogeneity multistate demographic models would seem to offer three advantages. First, it would make the models more realistic, and therefore make them more credible bases for policy recommendations. Second, it would invite the participation in multistate demographic analysis of sociologists and economists whose stock in trade is analysis of behavioral effects. Third, it would make it possible to address a much wider range of policy questions within the multistate demographic framework. The last point is quite important. Projections of long-run implications of current trends inform policy makers of impending problems but do not give information about the likely consequences of interventions. In most cases, policy makers cannot control the rates directly (e.g., rates of marital dissolution or of leaving employment) but can alter the distributions of characteristics that affect the rates (e.g., educational attainment, wealth, land holdings). Thus parameterizing the rates in terms of observables that are themselves potential targets of social policies sharpens the potential policy focus of multistate demographic analysis.

The remainder of the paper discusses a set of issues that are likely to arise in attempts at integrating event history models and methods into a multistate framework. As I see it, there are two distinct steps in this effort. The first involves adapting procedures for estimating causal effects on rates in the face of complications such as duration-dependence and unobserved heterogeneity to multistate demographic problems. The main lines of attack for this step are fairly obvious from current work. The second step is to construct a means of projecting the long-run implications of a set of rates. Since a realistic model may not be Markovian, the problem of projection may not be amenable to analytic solution. Instead, one may have to piece together predicted sample paths for diverse individuals in a fashion somewhat akin to what is commonly called microsimulation. The issues that pertain to forecasting or projecting in heterogeneous populations with non-Markovian rates seem far from clear at present.

2. PRELIMINARIES

Consider a random variable Y(t) that records the position of a unit at time t in a Ψ-dimensional state space. The set of states might consist of a set of regions and the state "dead", or a set of marital statuses. Because many demographic data sets record the flows of population over states for discrete intervals (often as long as 5 or 10 years), multistate demographic models have worked on the premise that Y(t) is governed by a *discrete time* stochastic process whose time structure is the same as the period of measurement. In fact, there is no constraint that durations of residence in a location or of a marriage have such a rigid time structure; changes of state on most demographic variables can occur at any time. Thus it is more realistic to assume that the underlying stochastic process has a *continuous time* structure, that the lengths of durations are nonnegative real numbers determined by some probability distribution. In addition to being more realistic, this structure turns out to be very convenient for forming estimators to work in a continuous time.* Therefore, I assume that Y(t) is a continuous-time stochastic process.

*One advantage of such a specification is that it gives a natural way to compare analyses of transitions over intervals of different lengths. This property facilitates comparisons between countries with different spacings of censuses for the same country over time. (France, for example, has used two different spacings between censuses in recent times and has asked questions about transitions over three different intervals.)

A realization of $Y(t)$, often called a sample path, records the times of all transitions and destinations. An event history describes the values of $Y(t)$ over some (possibly arbitrarily defined) observation period running from τ_1 to τ_2:

$$\omega[\tau_1, \tau_2] = \{y(t): \tau_1 \leq t \leq \tau_2\}$$

Events refer to changes in $Y(t)$. The time of the nth event is indicated by the random variable T_n. The starting date of the process is t_0, which is called for convenience the 0th event. Then Y_n, which equals* $Y(t+\varepsilon)$, is the random variable that records the state occupied just after the nth event. The random variable that records the length of time between the (n-1)th and nth events, the waiting time to the nth event, is denoted by U_n.

Empirical researchers often have complete records from the start of a process up to some arbitrary time (of measurement), τ_2. The event history over the period (t_0,τ_2) consists of the starting state, $y(t_0)$, the number of events in the period, $n = n(t_0,\tau_2)$, the timing of the successive events, $\{t_1,\ldots,t_n\}$ (or, equivalently, the waiting times between events), and the state entered at each event, $\{y_1,\ldots,y_n\}$. Thus the event history over the period can be expressed compactly as

$$\omega[t_0,\tau_2] = \{t_0,y_0,t_1,\ldots,t_n,y_1,\ldots,y_n\} \tag{1}$$

Notice that expression (1) does not contain the time of leaving the last observed state. That is, it does not contain t_{n+1}. There are two possibilities. If the state y_n is an absorbing state such as death, the record is complete. Since an absorbing state cannot be left, expression (1) contains all the relevant information about the history. If the state y_n is not an absorbing

*The stochastic process is assumed to be continuous from the right but discontinous from the left.

state but is simply the state that is occupied when the record ends, the event history in (1) is incomplete; it does not contain the full record of the sojourn in the state y_n, nor any information on subsequent behavior. Such an event history is said to be censored on the right. If the history begins at some arbitrary time, τ_1, (rather than t_0), it is also censored on the left.

Some demographic data contain complete (uncensored) event histories. For example, population registers permit reconstruction of complete residence histories of deceased individuals (individuals still alive at the time of measurement are right-censored). Likewise historical demographers have used parish records to reconstruct histories of marriage and fertility for local populations. More frequently, demographic histories are censored on the right. If, in addition, a retrospective history begins at some arbitrary date, the resulting histories will also be censored on the left. It turns out that right-censoring does not pose many serious analytic difficulties but that left-censoring is very problematic (see Tuma and Hannan, forthcoming, Ch.6). Thus for simplicity, I restrict discussion to the case where event histories are censored only on the right. In addition, I assume that the process generating censoring is independent of the substantive process under study. This assumption is clearly appropriate when data records are evaded by the analyst's decision, for example the decision to cease observation. It is potentially problematic when censoring reflects the decisions of the actors under study: for example, refusals to continue participation or disappearance. In such cases, censoring mechanisms may be related to the occurrence of events such as marital status changes. The preferred procedure for handling such endogenous censoring is to treat censoring as movement to a state and to treat the rate of movement toward the state as an explicit function of the causal factors being investigated. This allows one to explore the ways in which nonrandom censoring is likely to affect inferences about causal effects on other kinds of transitions.*

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*See Groeneveld et al. (1981) for an extended analysis of such problems in the context of SIME/DIME.

In many situations, the full details of an event history or sample path are not available. Sometimes only the frequency of each type of event over an interval (e.g., number of job changes) but not the timing of changes is known.* The most common data structure in the social sciences, panel data, contains even less information. A panel contains information on state occupancies at a set of (usually regularly spaced) arbitrary times, e.g., 1970, 1975, 1980. Such data arise commonly in censuses and in repeated surveys that do not ask the history of changes between surveys. A typical panel data record for an individual can be represented as follows:

$$\rho[\tau_1,\tau_K] = \{y(\tau_1),y(\tau_2),\ldots,y(\tau_K)\}$$

Clearly panel data contains much less information than event history data. The loss of information can be crucial in empirical work. Singer and Spilerman (1976) show that the loss of information about events between observations can cripple empirical analysis of even the simplest stochastic process, a stationary first-order Markov process. Specifically, empirical transition probabilities cannot necessarily be embedded in a continuous-time Markov process. Moreover, the estimates are quite sensitive to the spacing of observations. Such problems have been noted in the multidimensional demographic literature. For example, it has been shown repeatedly in migration studies that using flows over 1-year periods gives qualitatively different results than using flows defined over 5-year periods. Moreover it is known that estimates vary considerably when migrations are counted rather than migrants (one migrant may make several migrations in any period)--see Courgeau (1973) and Ledent (1980). The demographic literature has suggested some *ad hoc* solutions

*Tuma's (1981) RATE program performs maximum likelihood estimation of the effects of covariates on rates for this case called "change data", as well as for event histories. See Hannan and Freeman (in press) for an application to organizational mortality.

to the problems inherent in using panel data. However, multistate demography has remained wedded to the panel data format and a discrete-time structure. Indeed, even when event history data are available, demographers tend to ignore information on the timing of events.

It might be argued that demographers will continue to work in areas where only panel data (or aggregate flows over discrete periods) are available. Although this may be true, there has been a shift in large-scale survey research towards collecting complete (or fairly complete) event histories. For example, the U.S. Current Population Survey questions dealing with marital histories now collect the full histories. A number of labor force participation surveys also collect information on the timing of moves in and out of employment. Migration surveys are beginning to collect migration histories [for example, the RAND Malaysian migration study (Butz and DaVanzo, 1978) and recent French national surveys]. Moreover, there is an element of self-fulfilling prophecy to the assumption that demographers must be content with panel data. After all, demographers advise on the content of censuses and government funded surveys. If they were convinced that a great deal of analytic power could be gained by knowing the event histories of individuals, such questions might be incorporated in routine data gathering.

The following sections assume that event histories, censored only on the right, are available for analysis. There are enough complications in working through the details of this case without considering the further complications of panel data.

3. AN OVERVIEW OF EVENT HISTORY METHODS*

Event history data give an embarrassment of riches--there are many ways to describe empirical patterns. One way to procede is by imposing a model on the data. Before considering classes

*The materials sketched in this section are explored in greater detail in Part III of Tuma and Hannan (forthcoming).

of models, it is worth noting the main nonparametric approach to analyzing event histories. For simplicity I begin with the case of a 2-state "loss only" or "decrement only" process, where all units begin in a first state and transit at some random time to the second state where they are absorbed or trapped. The main descriptive statistic for the sample paths of such a process is the *survivor function*:

$$G(t|t_0) = G(u) = \Pr\{T \geq t\} = \Pr\{U \geq u\} \tag{2}$$

Kaplan and Meier (1958) proposed a nonparametric estimator of empirical survivor functions for right-censored data, which has become the standard tool of event history analysis. Let R_t denote the number of individuals exposed to the risk of having the event just before t, the so-called risk set, and let the ordered times of observed events be

$$t_1 < t_2 < \ldots < t_N \quad .$$

The Kaplan-Meier (KM) estimator is

$$\hat{S}(t) = \begin{cases} 1 & \text{for } t < t_1 \\ \prod_{j=1}^{i} \frac{R_j - 1}{R_j} & \text{for } t_i \leq t < t_{i+1}, \ i = 1,2,\ldots,N-1 \\ \prod_{j=1}^{N} \frac{R_j - 1}{R_j} & \text{for } t \geq t_N \end{cases}$$

Cases that are censored (lost to observation before the event) during that period drop out of the risk set but do not affect the estimated survivor function directly. The usual first step in event history analysis is calculation of KM estimates of the survivor function.

If the population under study were thought to be heterogeneous, one might disaggregate the population and calculate separate empirical survivor functions, and test the null hypothesis that the two random functions are the same. Figure 1 gives an example from the Seattle-Denver Income Maintenance Experiment (SIME/DIME) in which the distributions of survival times of marriages are compared for those couples on Negative Income Tax NIT) treatments and the control group. The sharp difference in the survivor functions suggests that the NIT program affected the distribution of lengths of marriages. This way of handling heterogeneity is compatible with current demographic practice. More generally one might disaggregate the population into fine-grained classes, e.g., white males between the ages of 30-35 who are married, have two children, a college degree, and are employed as engineers, etc. Separate KM estimators can be calculated for each subpopulation, and comparison of estimated survivor functions can be used to learn about differences in rates between subpopulations. This sort of nonparametric analysis of the effects of heterogeneity on rates is a useful point of departure when a huge number of observations are available (so that the survivor functions are not estimated over very small samples). However, it is often desirable to parameterize the effects of covariates and policy variables, to learn how the rates vary with quantitative variations in other variables. In the case of survey samples there is hardly any alternative to using parameterized forms for the effects of causal variables--survey samples simply cannot be partitioned into enough classes for there to be enough cases in each subpopulation for meaningful analysis.

Often substantive and policy questions direct attention to the effects of a set of variables on the process of change. One possible way to investigate such effects would be to express the functional dependence of the survivor function on a set of covariates. It turns out to be much more convenient to use an alternative representation, involving instantaneous transition rates or

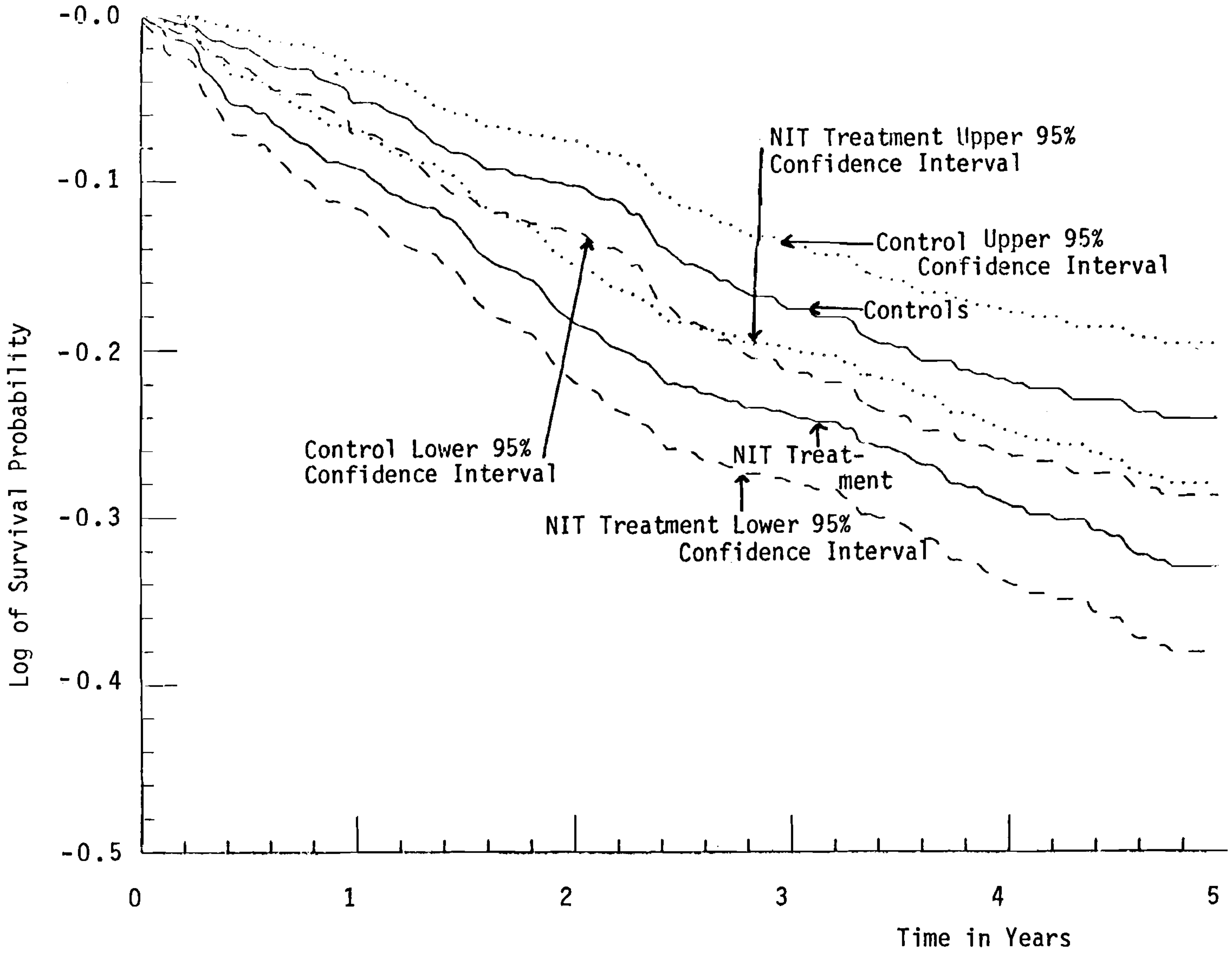

Figure 1. Estimated survivor plots of marriages of originally married white couples on SIME/DIME. Source: Groeneveld et al. 1981, p.56.

intensities.* In the simple model under consideration, the instantaneous rate (referred to here as rate for brevity) of moving to the absorbing state is defined as

$$
\begin{aligned}
r(t|t_0) &= \lim_{\Delta t \downarrow 0} \Pr\{ Y(t+\Delta t) = 2 | Y(t)=1\}/\Delta t \\
&= \lim_{\Delta t \downarrow 0} \frac{G(t) - G(t+\Delta t)}{G(t) \cdot \Delta t} \qquad (3) \\
&= - \frac{d}{dt} \log G(t)
\end{aligned}
$$

According to equation (3) the rate is the negative of the slope of the log-survivor function. Thus the negative of the slope in a plot of the log of the empirical survivor function against time, at any time t is a nonparametric estimate of the rate. In particular, if the log-survivor function is approximately linear, one can surmise that the rate is approximately constant over the period.

The methodology developed by Coleman (1964, 1981a, 1981b) for panel data and by Tuma (1976) for event history data centers on estimating parametric forms of dependence of rates on observed covariates, i.e.,

$$r(t|t_0) = f(\underset{\sim}{x},t)$$

where $\underset{\sim}{x}$ is a vector of (possibly time-varying) exogenous variables. To illustrate the derivation of the maximum likelihood estimator for this kind of problem, consider the special, but frequently used, case where

$$r(t|t_0) = \exp(\underset{\sim}{b}'\underset{\sim}{x}) \qquad (4)$$

*One possible point of terminological confusion between demographers and sociologists concerns the term "rate." Demographers use the term to refer to observed flows (counts of incidence relative to exposure). I use the term rate to refer to the quantity defined in (3), which is by definition not observable.

the $\underset{\sim}{x}$'s are a set of covariates that are constant over time but vary between individuals, and the b's are parameters that record their effects. The data consist of two kinds of observations. In the case of individuals who have been observed to make the transition from state 1 to state 2, the observed data are the times of the transitions (or the waiting times in the spells), say t_i for the ith individual, and the levels of $\underset{\sim}{x}$. In the second case are individuals who have not yet had an event by τ_1. One observes the length of the uncompleted spell and the level of $\underset{\sim}{x}$. Given the specification in (4), the probability of each type of event can be expressed as a closed form function of either t_i or τ_i and $\underset{\sim}{x}_i$ by solving (3) with initial condition $G(0) = 1$. Thus the likelihood function of the data can be expressed as a function of the observables and the parameters, and maximum likelihood (ML) estimates of the elements of $\underset{\sim}{b}$ can be found.

In addition to being concerned with the dependence of the rate on observable covariates, theoretical and policy questions are also sometimes concerned with the possibility of time variation in the rates. One way to investigate such questions is to examine the shape of the log-survivor function. However, in the presence of multiple covariates, some of which may be metric, this procedure is seldom feasible. An alternative estimates effects within some parametric form of time dependence. RATE (Tuma, 1981) performs ML estimation of a generalized form of the Gompertz-Makeham specification:

$$r(t|t_0) = e^{\alpha(\underset{\sim}{x})} + e^{\beta(\underset{\sim}{x})} e^{\gamma(\underset{\sim}{x})t} \qquad (5)$$

where $\alpha(\underset{\sim}{x})$ expresses the dependence of the "infant death rate" on the vector $\underset{\sim}{x}$, etc. This specification has been implemented empirically in studies of job mobility by Sorenson and Tuma (1978) and of organizational mortality by Carroll (1982) and Freeman and Hannan (1981).

Often there is no *a priori* information about the exact form of time variation in rates, but substantive arguments or prior research suggest certain qualitative patterns in rates. For example, Rogers and Castro (1981) argue that rates of migration shift at certain points in the life cycle. If one has a reasonably good idea about the times at which the shifts occur, the rate function can be specified as a step function, which is constant over periods but which shifts at the start of each new period.

The procedure for analyzing effects on such step functions, implemented in RATE, is also a flexible way to incorporate time variation in the causal factors. Periods of any desired length can be defined and the levels of some or all of the x's can change at the beginning of each period. In work on analyzing the effects of family income and transfer payments on marital stability, Groeneveld et al. (1981) divided the three-year observation period into 36 segments and changed the levels of all income-related variables at the beginning of each period. Moreover, RATE allows the analyst to impose the constraint that parameters are constant over any desired set of segments. Thus one set of parameters can be estimated for the entire period, covering all segments, or several sets of parameters can be used.

An alternative way of handling time-dependence of rates in the "loss only" context was developed by Cox (1972, 1975) for the case of proportional hazards with nuisance functions:

$$r(t|t_0) = e^{\underset{\sim}{b}'\underset{\sim}{x}(t)}\, h(t) \quad ,$$

where h(t) is the time-varying nuisance function, which varies only over time and not between units. This model combines a parametric specification of the causal structure and an unknown common time dependence (due, perhaps, to environmental variation). Cox's partial likelihood (PL) estimator gives consistent and asymptotically consistent estimates of the elements of $\underset{\sim}{b}$ even when h(t) is unspecified. This procedure is now very widely used in biometric analysis and has been used in social science research by DiPrete (1978), Hannan and Carroll (1981), Menken et al. (1981), and Coleman (1981b).

Thus the event history strategy has available an array of procedures for dealing with time variation in the rates. All three formulations can be addressed conveniently and efficiently within RATE.

Another line of work concerns *unobservable* heterogeneity in rates. Sociological interest in such models traces from Spilerman's (1972b) reformulation of the classic mover-stayer problem in these terms. An important recent development in this line of work is Heckman and Singer's (in press) nonparametric (EM) estimator for models with parametric forms for observables and an unspecified distribution of unobservables.*

Problems of describing and modeling event histories become more complicated and more interesting when "gains" as well as losses are permitted in the two-state model, producing an "increment-decrement" model. The added complication is that *history* may now play a role. The previous history of an individual at the time of event n is denoted by ω_{n-1}. The formal problem in the general two-state model is that $r_{12}(t|\omega_{n-j})$ need not equal $r_{12}(t|\omega_{n-k})$ for $j \neq k$. For example, the rate of leaving first marriages need not be the same as the rate of leaving second marriages. A reasonable starting place in analyzing the general two-state model is by comparing empirical survivor functions for first spells in the state, second spells, etc. If they are reasonably similar, one might want to pool spells and assume that they are governed by a single set of parameters. If they differ, one must investigate why. A possible reason for differences across spells is that the distributions of observables and unobservables differ for first versus second spells, etc. An alternative possibility is that history *per se* affects

*For additional work on unobserved heterogeneity, see Chamberlain (1979), Tuma (1980), and Vaupel et al. (1979).

the process--experiencing an event once alters the rates for subsequent episodes.

At the moment there is no general theory about how to test between these alternatives. In practice, researchers sometimes pool spells, add to the set of observed covariates a variable that indicates whether the spell is a first or subsequent spell, and test the null hypothesis that the parameter associated with history is zero. More generally, the null hypothesis of one common set of parameters can be tested against the alternative hypothesis that all (or some) of the parameters for first spells differ from those for subsequent spells. The latter procedure allows for a richer set of historical interactions than does the former. If, in the end, the process really does seem to depend upon history, there is no alternative but to model first events differently from second events, and so on.

The final step in increasing the generality of the problem is to allow the model to have Ψ states. Now the *destination* of a a move as well as its timing is a random variable. As I mentioned in Section 1, Tuma (1981) and Tuma et al. (1979) generalized the methodology for the typical two-state model (discussed widely in biometrics) to this case. The generalization involves defining event-specific survivor functions, $G_{jk}(t_n|\omega_{n-1})$, which record the probability that an episode that begins at t_{n-1} in state j and ends in a move to state k will last at least as long as $u = t_n - t_{n-1}$.

In formal terms there is a competing-risk problem.* One way to think about the situation is to imagine that there is a race among Ψ competitors and that only the winner's identity and time are recorded. The parallel is that Ψ realizations of the random variables are drawn and only the smallest of those is recorded. In particular if the Ψ processes are independent, the unconditional

*See Elandt-Johnson and Johnson (1980) for a good introduction to analysis of competing risks.

survivor function for episodes in state j is equal to the product of all conditional survivor functions:

$$G_j(u|\omega_{n-1}) = \prod_{k=1}^{\Psi} G_{jk}(u|\omega_{n-1})$$

In the simple case of independent competing risks, the conditional survivor function can be estimated by slight modifications of the Kaplan-Meier estimator (which involve conditioning on the type of transition). Thus empirical conditional survivor functions can be estimated for the $\Psi^2 - \Psi$ possible transitions. By analogy to the two-state case, an instantaneous transition rate may be defined as:

$$r_{jk}(t|\omega_{n-1}) = r_{jk}(u|\omega_{n-1}) = \lim_{\Delta t \downarrow 0} \frac{P_{jk}(t,t+\Delta t|\omega_{n-1})}{\Delta t}$$

where

$$P_{jk}(t,t+\Delta t) = Pr\{Y(t+\Delta t) = k | Y(t) = j\}$$

In other words, the instantaneous transition rate is the limiting transition probability. As in the two-state case, there is a simple relation between the estimable (conditional) survivor function and the transition rate:

$$G_{jk}(t|\omega_{n-1}) = \exp\left[\int_{t_{n-1}}^{t_n} r_{jk}(s|\omega_{n-1})ds\right] \qquad (6)$$

The relationship in (6) serves as a basis for empirical estimation.

Sometimes for modeling, it is convenient to use an alternative parameterization of the rates. Let $h_j(u|\omega_{n-1})$ denote the density of the waiting time distribution for episodes in state j; this function is commonly called the *hazard function* for state j. Let $m_{jk}(u|\omega_{n-1})$ denote the *conditional transition probability*, the conditional probability that a move occurs from j to k given that state j is left after duration u. Then, it follows that

$$r_{jk}(t|\omega_{n-1}) = r_{jk}(u|\omega_{n-1}) = h_j(t|\omega_{n-1})m_{jk}(t|\omega_{n-1})$$

This specification is valuable when substantive arguments imply that some covariates affect only the rate of leaving a state but not the conditional probability of moving to one destination rather than another or that some covariates influence the destination but not the rate of leaving the destination. Such arguments sometimes follow from conceptualizing decision making as a two-step process, where one first decides whether or not to move and then, as a condition to that decision, decides on a destination. Spilerman (1972a) used this sort of representation and argued that unobserved heterogeneity affected the hazard functions but not the conditional transition probabilities.

The ML and PL estimators discussed above have been generalized to this multistate case of independent risks and have been implemented by Tuma (1981). Thus one can parameterize explicit causal effects, parametric and nonparametric time dependence of rates, and effects of unobserved heterogeneity.

This framework has been used to analyze marital status change (Hannan et al., 1978), movement between employment and nonemployment (Tuma and Robins, 1980), migration (Keeley, 1980), job change (Tuma, 1976; Sorensen and Tuma, 1978), organizational mortality (Carroll, 1982; Freeman and Hannan, 1981), and change in national political structure (Hannan and Carroll, 1981). Some of these analyses concentrate mainly on the effects of observed covariates, using a variety of nonlinear specifications. Others introduce time dependence and/or unobserved heterogeneity into models with observed covariates.

Little attention has been paid to the problem of non-independent risks in the social science literature. However, Holt (1978) shows that Cox's PL estimator may be adapted to provide consistent estimators of causal effects in a model with dependent competing risks. This strategy ought to be explored because the problem of competing risks being dependent is a plausible complication in most applications of multistate demography.

4. CONFRONTING THE MARKOV MODEL WITH EVENT HISTORY DATA

The analytic power of multistate demographic models comes from the assumption that transitions follow a time-homogeneous Markov process. The assumption of time homogeneity allows projection of a population over long periods using a current set of rates. The Markov assumption permits the analyst to ignore previous history and to treat all episodes in a state as homogeneous. With these two assumptions, numerous functionals of the stochastic process can be calculated in a way that parallels the simpler, decrement-only case (where, by definition, there is no previous history of the event in question).

By now numerous doubts have been expressed that any social process obeys the Markov assumption (see Hoem, in press and Heckman and Singer, in press). The realism of the Markov assumption seems to be a problem in multistate demography. Thus a first step in any use of event history data in multidimensional demography should be some nonparametric testing of implications of the Markov assumption. The classic test examines whether the product of estimated transition matrices for two successive periods equals the transition probability matrix estimated for the period that spans the two initial periods [see Singer and Spilerman (1976), Singer and Cohen (1980), and Cohen and Singer (1981) for a full exposition of this approach]. Singer (1980) also suggests tests that use the sequences of events to test for the dependence on history. Under the Markov assumption, the expected sequences of events follow a simple probability structure that can be compared with the observed distribution of sequences.

Unfortunately the simple, available procedures for testing the Markov assumption assume a homogeneous population. In the more general case considered here, the population contains both observed and unobserved heterogeneity. Failure to incorporate such heterogeneity can account for apparent failures of the Markov assumption. Thus social researchers should build a fairly realistic model of the effects of heterogeneity before testing the implications of the Markov assumption. One way to do so is to estimate the parameters of the process from first episodes and use these estimates together with observed distributions of covariates for second spells to predict the empirical survivor function for second spells.* At any rate, I would recommend that attempts to verify implications of the Markov assumption be made *after* the behavioral model for the rates has been specified.

Still, the expectation that the Markov assumption is not realistic suggests that an agenda for future research should be capable of dealing with models that make weaker assumptions. Although many possible approaches might be tried, there are two obvious alternatives. One involves tinkering with the existing model, gradually weakening assumptions and comparing predictions with data until some more realistic model is obtained. It seems that one might profitably begin with a semi-Markov specification (as advocated by Ginsberg, 1971; Hoem, 1972; and many others). The second strategy works from the bottom up. It builds behavioral models for rates of various types of transitions, testing for effects of history and including them when doing so appears to be necessary to fit the data. The final stage of the second approach involves putting together the pieces to form some overall model of the process.

The remainder of this paper concentrates on the second approach, the patchwork quilt strategy. This style of work differs more in spirit from the prevailing traditions in both conventional and multistate demography and may clarify the potential value of event history methods for demographic analysis.

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*See Tuma et al. (1979) for an illustration of predicting survivor functions.

5. TWO EXAMPLES

In order to make the methodological issues concrete, this section describes two substantive examples. The first is an empirical study of transitions in a multistate framework, involving employment statuses and marital stability. The second example, which has not yet been used empirically, suggests how to extend the framework to analyze migration.

5.1 Employment Status and Marital Stability

An extensive social science literature shows that rates of marital dissolution vary substantially with social class. Moreover, employment statuses of both spouses affect rates of dissolution. While a husband's employment tends to lower the rate, a wife's employment tends to raise it, at least in the U.S. At the same time, marital status strongly affects the probability of being employed, which, in turn, depends on rates of entering and leaving employment; married men have higher probabilities of employment than comparable single men, and married women have lower probabilities than comparable single women.* Thus marital status and labor supply appear to be a *coupled* pair of qualitative states--the rates of change on each depend on a person's position on the other.

The coupling of the two processes posed an analytic challenge in analyzing the impacts of the Negative Income Tax Experiments mentioned above. The initial empirical work in these experiments dealt essentially with what might be termed reduced forms. One group of researchers studied the impact of the experimental treatments on the rate of marital dissolution, holding constant *initial* employment status of husband and wife. Another group studied the effects of labor supply (both hours of work and employment status) holding constant *initial* marital status. The reduced-form analyses revealed that the treatments increased rates of dissolution. The treatments also lowered rates of entering employment, thereby increasing durations of unemployment. But, because

*Labor economists tacitly recognize these differences by estimating separate labor supply functions by marital status for each sex.

the two processes may be coupled, reduced-form estimates are hard to interpret. Perhaps all of the observed response reflects the labor-supply response. In such a case people adjust employment status (a direct effect), which in turn induces some changes in marital status (an indirect effect). Alternatively, there may be no direct effect on employment status, only an indirect effect via marital status changes. Answering questions of policy interest requires separating the direct and indirect effects of the treatments. This means estimating effects of the treatments on the coupled process directly.

Tuma et al. (1980) used the following approach to estimate the direct effects of the treatment on rates of marital dissolution. They defined the five state process diagrammed in Figure 2 where the state "dissolution of marriage" is treated as an absorbing state. Note that the eight rates running around the "outside" of the diagram concern the coupling of changes in employment of

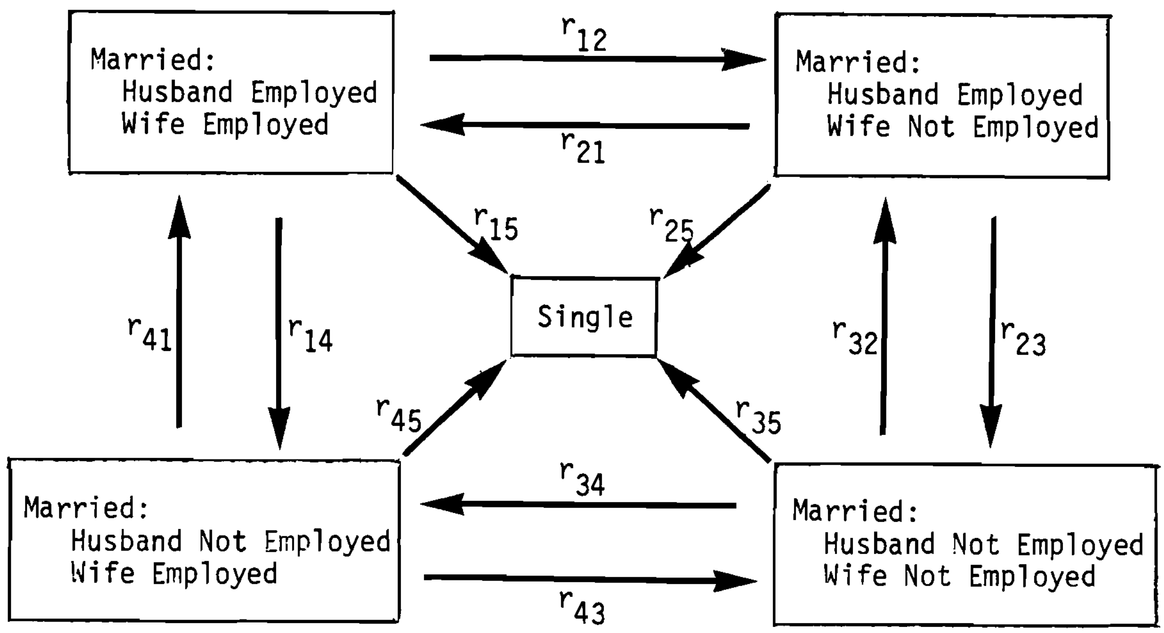

Figure 2. Illustration of a possible (partial) state space for analyzing the effects of spouses' employment statuses on rates of marital dissolution (becoming single).

statuses of spouses. For example, a comparison of r_{21} with r_{34} tells whether a husband's employment affects his wife's rate of becoming employed. The rates of interest here are the four rates running towards the state "dissolution of marriage."

Consider the two polar situations. The first extreme is that the treatment has *no* direct effect on the rate of dissolution. In this case, the estimated effects of the treatments on the four rates would be essentially zero within sampling variability; the reduced-form effect would be due to differences between the four rates and to the direct effects of the treatments on the rates of moving among the four states on the "outside" of the diagram. In other words, the experimental treatment may simply shift couples to states in which the risk of marital dissolution is higher, without changing the risks *per se*. The opposite extreme is the possibility that the marital stability response does not depend at all on changes in employment statuses. In this case, the estimated effects of the treatments on all four rates would be approximately the same; they would be equal to the reduced-form effect.

Tuma et al. (1980) actually estimated a hierarchy of models that contained these polar extremes as well as some other cases. It turns out that the NIT treatments do have substantial direct effects on rates of dissolution. For the sample of white couples in SIME/DIME, the findings are quite close to the second case mentioned above. That is, the effect of the NIT treatment on the rates of dissolution does not vary much with employment statuses of spouses. However, for the sample of black couples, the effect does depend on employment status. For reasons that are still little understood, the direct effect of the treatment in the case of the black sample is much stronger when the wife is not employed.

In addition to the findings regarding direct effects of treatments, the analysis also examined the effects of employment statuses themselves on rates of dissolution. The findings agree with the qualitative literature. A husband's employment tends to stabilize a marriage but a wife's employment tends to destabilize it. And, since Tuma and Smith-Donals (1981) found that marital status affected rates of change in employment status, the two basic processes do seem to be coupled. Something like the 5-state model used here or some generalization of it seems necessary for analyzing the evolution of employment and marital statuses in a population.

5.2. Migration

Suppose one were to mount a similar attack on migration rates. What kind of specification would be appropriate? The literature on migration seems to have two views of the subject. One view is that migration rates depend mostly on age: that migration rates rise sharply in the late teenage years, drop again in midlife, and rise slightly in old age (see the review and evidence in Rogers and Castro, 1981). The other view, reflected mainly in the literature on migrant selectivity, claims that heterogeneity within the population strongly affects migration rates. This literature argues that migration rates depend on education, information about opportunities, presence of relatives in destinations, etc. Of course, the two views are not as different as they might seem. The arguments for age-dependence refer primarily to *events* in the life cycle, which tend to cluster at certain ages, e.g., leaving school, entering full-time employment, getting married, having children, retiring. Since these events do not occur to all members of real populations and happen at different times to different persons (in ways that vary according to social class), age-dependence in rates can be viewed as an implication of unobserved heterogeneity that varies over the life cycles. On this interpretation, models for migration rates might incorporate *explicitly* information about the timing of the events that affect migration rates. One way to do so is to use the kind of analytic strategy sketched out for the first example.

Consider the highly simplified model of migration in Figure 3 for one sex over a generation. The model includes information on schooling, marital status, and rural/urban residence. To simplify exposition, the model assumes that school cannot be reentered once it is left and that only one status can change in any instant. Two of the rates r_{12} and r_{21}, pertain to migrations that

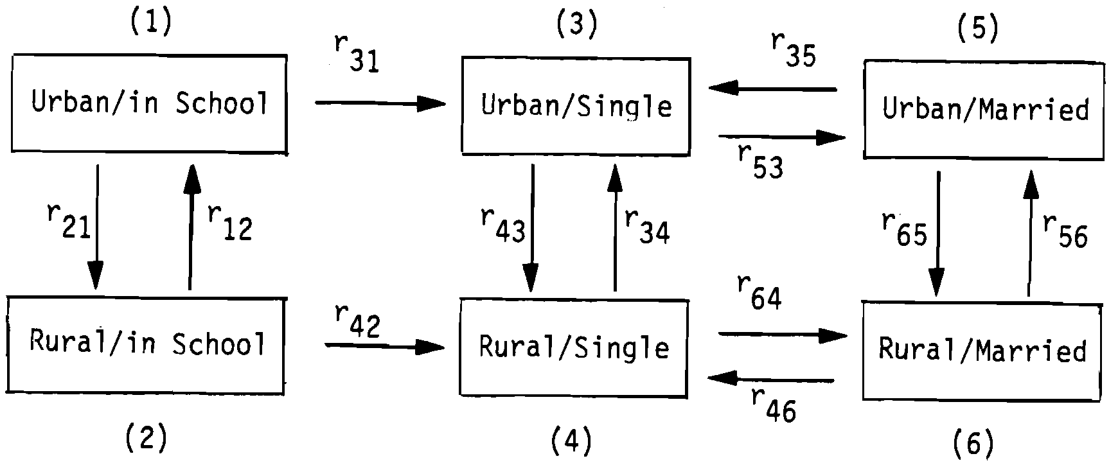

Figure 3. Illustration of a possible state space for analysis of the effects of school attendance and marital status on urban-rural migration.

occur during schooling. It seems natural to assume that these rates depend on parental characteristics, e.g., social class, but not on the individual's age or characteristics. Four other rates characterize migration between urban and rural places. If marital status does not play a role in the migration process, these four rates will collapse to two. Thus the question of age effects versus marital-status effects can be addressed by estimating models with four rates and comparing fits with models that constrain $r_{34} = r_{56}$ and $r_{43} = r_{65}$. If the fit of the constrained model is much worse than that of the unconstrained model, one would conclude that marital status affects migration net of age. Alternatively, this procedure might be turned around to ask whether age affects migration rates net of the effects of marital status.

A number of other covariates in addition to age might be included explicitly in the four adult migration rates. Some covariates would typically refer to characteristics that are fixed for persons, for example, sex, race, ethnicity, parents' social class, place of birth. Other relevant covariates typically change during lifetimes, for example, wealth, occupation, family size. Including time-varying covariates requires either a specification of the times at which they change or some assumptions about typical time-paths of change, for example, linear change in wealth between observations.

The literature disputes the existence of effects of duration of residence on migration rates. Morrison (1967), McGinnis (1968), Ginsberg (1971), and Hoem (1972), among others, have argued that the rate of migrating declines with time spent in a place. But, Clark and Huff's (1977) reanalysis of microdata concludes that such effects play a very minor role in migration processes. It would be interesting to address this question with event history methods. A reasonable specification is the generalization of the Makeham-Gompertz model mentioned above in equation (5). Analysis with such a model could include age and other observable covariates in the time-independent and time-dependent portions of the process.

Perhaps duration does affect migration rates, but the "clock" restarts with major life events such as the beginning or ending of a marriage. Even if there is some overall "cumulative inertia" effect such that the rate of migration declines with length of residence, the social ties that bind a person to a place tend to get reorganized when marital status changes.* Perhaps the migration rate of a newly married 20-year resident is just as high as that of newly married 5-year resident, even though their rates differed sharply prior to the marriage. It is straightforward to test hypotheses about such duration effects with RATE.

*Courgeau (1980) discusses the possibility that marriage and migration are dependent processes.

6. A SUGGESTED HIERARCHY OF MODELING ISSUES

Dropping the assumption of a homogeneous population responding in terms of age-varying but otherwise constant rates opens Pandora's box. Section 2 listed four types of complications that have already been addressed in social science applications of event history methods: observed heterogeneity, unobserved heterogeneity, time-dependence (calendar time), and duration-dependence rates. Even if a realistic model will include all four types of complications, it is not advisable to begin with specifications with full-blown complexity. The present state of knowledge in the social sciences does not permit the number of *a priori* restrictions on parameters that would be needed to identify such a model. Moreover, the models would be so complex that it would be hard to learn anything about model specification from the study of the fit of the specifications of the model to empirical survivor functions. Thus some broad strategic decisions about the hierarchy of complications must be made prior to beginning any line of anlaysis.

One can imagine beginning with any one of the complications taken alone. Indeed, the papers cited in earlier sections show the full range of possibilities here. Some add only unobserved heterogeneity; others add only duration-dependence, etc. If each complication had unique empirical indications, the order of introducing the possibilities would make no difference. Unfortunately this does not seem to be the case. Each of these complications can give rise to the same empirical indications. Ignored heterogeneity makes rates change systematically with duration and time; ignored time-dependence or duration-dependence gives rise to spurious heterogeneity between populations with different distributions of duration or of periods of exposure. Therefore it is probably not illuminating to cycle through an analysis that considers complications *seriatum*. Such an exercise cannot tell whether the same complication has manifested itself in different forms or whether each of the types of complication actually exists.

The alternative is to impose some sort of hierarchy, to pick an issue and conduct an empirical analysis of specifications appropriate to that issue. Once a specification looks promising, add the next higher-order complication, and so forth. Of course, this strategy can missfire. There is no guarantee that one will not mistakenly attribute an empirical pattern to a process. Still, this kind of discipline makes it possible to work systematically, learning about the process by making modifications in the specification and observing improvements in fit.

Is there any natural ordering of complications for the typical multistate demographic problem? There is probably little agreement on this matter. I suggest that population heterogeneity stands at the top of such a hierarchy in both basic and applied research. Models gain both analytic power and policy relevance as postulated unobserved effects are parameterized in terms of observable, measureable variables. Indeed, duration-dependence and time-dependence are summaries for a number of postulated causal processes. Measuring the variables involved in such processes allows much sharper discrimination among classes of models. Likewise, a natural response to the existence of unobserved heterogeneity is to try to observe it, to take measurements, and to parameterize the heterogeneity in terms of the measured variables. In other words, the natural progression of a modeling effort involves increasing emphasis on parameterization of effects in terms of measured variables. Therefore, why not begin with an emphasis on the effects of measured heterogeneity?

An emphasis on measured heterogeneity has several consequences that merit its use as a point of departure. First, it keeps attention on the need for measuring the relevant characteristics of actors and of the environments. Rather than delaying interest in collection of appropriate measurements on covariates until a late state of the research process, it has this emphasis from the start. Second, it forces researchers to specify causal processes in terms that could be measured in principle, even if data are not available at present. Third, it gives intermediate products that have potential policy applications. Since policy makers can sometimes alter the distributions of the covariates that are commonly measured, e.g., education or wealth, it is informative for policy discussions to know how the rates vary with the levels of such variables.

For these reasons I advocate directing attention initially to collecting observations on relevant covariates and parameterizing effects of observables on rates. As the examples in the previous section suggest, there are two broad approaches to using such information. One may assume that the system is recursive, that changes in the covariates affect the rates but that changes in the process of interest do not have feedback effects on the covariates. Or, one can assume that some of the dimensions form a coupled system, as in the examples discussed in the previous section.

For at least some of the substantive multistate demographic problems, the natural progression is from observable heterogeneity to duration-dependence of rates. For example, theoretical arguments suggest that rates of marital dissolution will fall with duration because marriage-specific capital accumulates (Becker, 1981). Empirical work supports this view (see, for example, Hannan et al., 1978). Likewise, economic theory predicts that rates of leaving unemployment will rise with duration because the reservation wage will fall (see Lippman and McCall, 1976). This prediction, too, has received support in models with appropriate covariates (see, for example, Heckman and Singer, in press).

The unexplained portion of a process with covariates and duration-dependence reflects three kinds of effects: period-specific effects common to all actors, actor-specific effects that are constant over periods, and effects that vary over both periods and actors. The first kind of disturbing influence can be handled effectively with Cox's partial likelihood estimator. Thus this problem can be addressed within the context of the two classes of analyses already discussed.

The effects that are specific to individual actors can be handled parametrically with RATE or nonparametrically with Heckman and Singer's adaptation of the EM algorithm. As long as this heterogeneity is orthogonal to the time-varying noise function, there seems to be no difficulty in principle in combining the two kinds of complications.

The suggested scenario for empirical model specification goes as follows. Begin with models with observed covariates, estimate effects with ML and PL methods, search for specifications that agree with substantive theory, and produce good fits to the empirical survivor functions. Second, add duration-dependence (perhaps in the general Makeham-Gompertz form), allowing covariates to affect both the time-dependent function and the duration-varying function driving the rates. Again, both ML and PL procedures may be used. Third, introduce the assumption of unobserved heterogeneity that varies only between individuals and reestimate the models using Heckman and Singer's nonparametric EM estimator. Comparison of estimates and fits to empirical survivor functions at this point may suggest some respecification involving observed covariates and duration-dependence, at which point the cycle can begin again, preferably on a different data set.

7. PROJECTIONS

The distinctive feature of multistate demography is its ability to project over multiple states for long periods. This characteristic makes it a potent tool for understanding the long run implications of a set of rates. If event history analysis is to enrich this approach, it must lead somehow to comparable projections. One problem is that investigation of the structure of rates of change may not support the contention that the rates have a particularly simple form. For example, dropping the assumption of time-homogeneous Markovian rates makes projection a much more complicated game. It is far from clear how to make projections for heterogeneous populations with age-varying, duration-varying rates, history-dependent even for one generation. In the interest of stimulating thought on this important topic, this section outlines a possible approach, which elaborates one already used in a short run context by Groeneveld et al. (1980).

Policy makers often want to obtain information about the costs of particular social policies or of alterations in existing policies. The earliest attempts to answer such questions were based on an "accounting" perspective. The accounting approach tried to enumerate the people who received benefits under a present program weighted by benefit levels and compare the total with a similar calculation made for an altered program. This style of policy analysis lost favor in the mid-1960s when social scientists began to argue that this approach was misleading because it tacitly assumed that changes in policy do not affect behavior. If, as often seems likely, changes in policies induce behavioral response, one must forecast the response in order to enumerate the population of potential beneficiaries. For example, if the provision of welfare benefits tends to reduce labor supply, a quantitative estimate of the expected response to a change in welfare benefit levels is needed in order to determine the number of persons who would be expected to receive payments. For example, the provision of a form of income support might induce some individuals to drop out of the labor force, thereby increasing the number of persons eligible for maximum payments.

Orcutt (1957, 1960) developed an approach for combining empirical estimates of behavioral responses with information on population distributions to answer policy questions from a behavioral perspective. The approach, called microeconomic simulation or microsimulation has become a major tool of policy analysis in the U.S. in recent years (see, for example, Haveman and Hollenbeck, 1980a, 1980b). The basic idea is to formulate behavioral models of response that are parameterized in terms of variables for which population distributions are known (e.g., family size, age, income, race) and to estimate the models from available microdata (often using different data sets to estimate different response parameters). Such estimates are used to forecast behavioral responses in the whole population, using known distributions of the covariates [available censuses or the Current Population Survey (CPS)]. Taking into account the behavioral response, the cost of the program can be calculated at the level of the individual family and aggregated to the national level.

One version of microeconomic simulation, the Urban Institute model (Orcutt et al., 1976), deals with changes in household composition. The model amounts to an implicit multistate demographic projection for a heterogeneous population. It applies to each family in the CPS a set of transition probabilities pertaining to changes in the composition of the household: birth rates, death rates, rates of marital dissolution, marriage rates, etc. These transition probabilities are assumed to depend on age, income, education, and so forth. An estimated transition probability is calculated for each combination of the covariates and is compared with a draw from a uniform distribution over [0,1]. If the probability exceeds the chosen random number, an event is assumed to have occurred; otherwise one assumes that there was no change in state. Finally, events are weighted according to the level of the national population using known sampling weights for the Current Population Survey.

When this procedure is applied to periods longer than one period (usually a year), it relies implicitly on the assumption that the stochastic process generating events is a time-homogeneous Markov process. The same set of rates are applied in each year and the evolution of the population over the states is computed. If the procedure were extended over along period, it would parallel a multistate demographic projection using Rogers's approach. However, it differs from multistate life table analysis in that it includes the effects of observed heterogeneity in transition probabilities.

Groeneveld et al. (1980) modified the Urban Institute model to simulate the effects of Negative Income Tax plans on rates of marital dissolution in the U.S. population. The portion of the Urban Institute model that deals with changes in marital status was respecified in *continuous time*, with the observed characteristics of persons (couples) affecting rates. Instead of simulating events period by period, a length of the waiting time in the spell was projected for each person (couple). Recall that an empirical survivor function, such as the one in Figure 1, maps from time to survivor probabilities. The projection method uses the inverse mapping. A number is chosen from a uniform [0,1] distribution for each person (couple) and the inverse mapping is solved for t (the time of the simulated event). In the case of competing risks, all of the latent survivor functions are used and only the smallest of the t's is assumed to define an event.

Groeneveld et al. (1980) used this procedure on the CPS sample and generated projected times of marriage and marital dissolutions for all adults in the CPS sample under a variety of NIT programs. The Markov assumption was invoked to allow simulations to multiple spells for individuals from one set of rate functions so that the entire period of projection was filled in. The resulting sample path projections tell the location of every sample member at each moment over the projection period. This data can be summarized in a variety of ways to suggest the likely impacts of the different programs, e.g., changes in the fraction of the population in the state "married" over time or number of dissolutions over the period.

The idea of simulating *sample paths* for members of heterogeneous populations forms the basis of a possible approach to multistate demographic projection. The example mentioned above was highly simplified. In particular, it concentrated on a two-state Markov model. The approach can be easily generalized to the case of multiple events, however. Equation (6) can be used to simulate the waiting time in each state using empirical waiting time functions and simulate destinations, conditional on the move, using empirical conditional transition probabilities.

There is no difficulty *in principle* in including effects of history. If the sample over which rates are estimated is large, separate waiting time distributions and conditional transition probabilities can be estimated for different observed histories, e.g., rates of dissolution can depend on the number of previous marriages. Then, in simulating sample paths, waiting times and transition probabilities appropriate for the number of the current marriages can be used in projecting events in the current spell.

The steps involved in this sort of projection are as follows:

1. estimate parameters of transition rates (or waiting time distributions and conditional transition probabilities) from available microdata, using covariates that have analogues in the population enumerations;
2. choose a standard population, e.g., a CPS sample, for which the joint distribution of the most important covariates is tabulated;
3. calculate rates (or waiting times and conditional transition probabilities) for each sample member;
4. pick numbers from a uniform distribution, simulate episodes and transitions for each individual, creating a projected sample path;
5. using sampling weights, weight-up to the population level; and
6. summarize the evolution of the distribution of the population over states.

When the goal of the projection is analysis of the effects of some sort of social policy, two modifications may be made. If the social policy is designed to alter a particular set of parameters, one may make such changes and compare the results with the baseline projection. If the social policy is designed to change the level or distribution of one or more of the covariates (e.g., income, education), the standard set of the parameters can be applied to changed distributions, giving a new set of sample paths that can be compared with the standard set. More realistically, a random rule might be used to reallocate income or to assign additional schooling to individuals.

An advantage of this approach to projection is that it emphasizes the randomness in typical social processes. Rather than giving each individual his/her expected values, random events are simulated. This means that it is possible to learn something about the *variability* of projections with the same set of parameters (which is not possible with current methods). If sufficient resources are available, multiple sample paths can be simulated for each individual, using different random numbers. Each set of paths for the sample of individuals gives one description of an outcome to the sample. The description given by different runs can be compared to learn how wide is the band within which the aggregate process fluctuates.

Indeed, one can go further and introduce unobserved heterogeneity at the individual level. Suppose the assumption that unobservables have a gamma distribution with certain parameters gives a good description of the microdata. This information can be used in projections. Instead of treating the waiting time for each combination of observed covariates as a constant, treat it as a random variable with the prescribed gamma distribution. Multiply each individual's rate (given by the observables and the parameters) by a draw from the gamma distribution and then procede as before. Now there are two sources of random variation in the projection; and one can experiment to learn about the sensitivity of the global features of the projection to unobserved heterogeneity.

8. DISCUSSION

This sketch of a merger of event history analysis and multistate demography has traced only some of the main contours of a strategy. Many conceptual and practical problems have not been addressed explicitly. This closing section briefly discusses some of these issues.

Perhaps the most pressing conceptual problem is the so-called two-sex problem. The approach suggested above traces the movement of a single sex over statuses until death. In order to consider more than one generation, births must be added to the model. This extension makes analysis very complicated. In human societies births are typically couple-specific events in both a biological and social sense. Therefore, modeling births requires assumptions about the sorting of men and women into pairings (marriages). When one ignores the sorting process and simply projects each sex separately over the states of single and married, there is no guarantee that the number of marriages will be equal for the two sexes at any time. Indeed, the probability that they will be equal is vanishingly small. Thus there will generally be an inconsistency between the two single-sex analyses and projections. Among other things, this means that there is no meaningful way to assign births to the two sexes.

The standard demographic solution to this problem is to throw the men out of the model, to consider women giving birth to daughters and, using known sex ratios, to inflate numbers of women to the numbers in a two-sex population. This is also the implicit strategy used in the Urban Institute microsimulation model. Each woman is assigned a "ghost spouse" at the beginning of the process, using rules that reflect the covariance structure of characteristics of spouses in observed marriages. As a woman is projected through the states of married and single, the ghost spouse is turned on and off. In other words each woman is given a set of husband's characteristics, which operate whenever she is married by the simulation rule. Although men appear as actors in other portions of the model, they are indeed ghosts from the perspective of marriage and fertility. In particular, the distributions of characteristics of eligible mates does not affect the kind of marriage partner a woman will have; she always marries the same husband.

The comparative statics of marriage markets, where men and women compete for desirable partners, forms the basis of Becker's (1981) theory of marriage. This theory directs attention to the dependence of sortings of men and women on availabilities (e.g., the shape of the age-sex distribution) and on productivities of men and women. Sanderson (1981) has developed a two-sex marriage model using somewhat weaker behavioral assumptions. The model assigns men and women, characterized by age, to marriages or to the single state. It traces the effects of changing age structures on equilibrium matches and on the incidence of marriage.

It seems natural to adapt two-sex marriage models and incorporate them in multigeneration-multistate projections in order to eliminate the ambiguities of the one-sex approach. Although this would be highly desirable, it is not simple. Whereas the approach discussed in earlier sections is probabilistic, the available two-sex marriage models are deterministic. Indeed it is the determinism of the Becker and Sanderson models that guarantees that equal numbers of men and women marry. Men and women are assigned to marriages and a constraint is imposed to force the numbers of marriages in each sex to be equal; there is no indeterminacy. But, what happens if one simply lets the probability (or rate) of making a certain type of marriage depend on the distributions of characteristics of competitors and of eligible mates? Any random rule applied to men and women will produce the kind of inconsistencies mentioned above. How can random marriage models be constrained to equalize numbers of men and women marrying? As far as I know, this question has not yet been answered.

If this analysis is correct, the study of marriage markets will play a key role in multistate demographic analysis designed to answer questions about changes over generations. In particular, the differences between the deterministic optimal sorting models and stochastic models for rates must be clarified.

There are also numerous methodological problems that require additional study. I have already mentioned several of the most pressing problems: nonindependence of competing risks, left-censoring of event histories, endogenous right-censoring, and the general problem of discriminating heterogeneity from time-dependence (or duration-dependence). While work on these problems has barely begun, there is no need to delay implementing event history methods in demography until the problems have been solved. The available procedures of event history analysis have already been shown to work well relative to conventional methods of longitudinal data analysis. Moreover, serious application of these methods to problems in multistate demography will almost surely hasten methodological advance.

The main argument of this paper is that multistate demographic analysis could be strengthened greatly by incorporating recent developments in longitudinal data analysis, specifically methods for utilizing the full details of event histories. An implication of the argument is that demography has much to gain from collecting more "life histories" which record the dates of key demographic events such as migrations, marital status changes, employment changes, and fertility. Full use of such data requires shifting from discrete-time to continuous-time stochastic models. It also almost surely requires attention to heterogeneity within populations. At the same time, the potential value of event history models and methods for policy analysis will be enhanced if methods of projection can be developed to parallel the projections of multistate demography. Use of continuous-time models within a "microsimulation" approach (which is simulating sample paths) seems to offer some potential along these lines.

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