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ABSTRACT

STOCHASTIC MODELS OF SOCIAL MOBILITY:
A COMPARATIVE ANALYSIS AND AN APPLICATION
TO JOB MOBILITY OF MEXICAN-AMERICAN MEN

By

Nancy Brandon Tuma

This research has two main aims: (1) to analyze and compare previously-proposed stochastic models of social mobility possessing a Markovian interpretation, and (2) to apply these models, insofar as possible, to job mobility of a sample of 584 Mexican-American men with a high school education or less who resided in selected Michigan counties during the winter of 1967-1968.

It is first shown that one can separate the process of individuals leaving social positions from the process of individuals entering new social positions, given that they are leaving other social positions. This division facilitates the comparative analysis of mobility models.

The innovative features of most previous models pertained to the process of leaving a social position. The natural assumption is that an individual's probability of leaving a social position is a time-independent constant (designated Probability Law I). Past predictions based on this law have consistently been poor. To improve predictions, three approaches have been used: the assumptions of nonstationarity (time-dependence), of population heterogeneity, and of stages within a social position. Each approach has been used to construct various models of the leaving process; however, several models imply the same probability law. In all, six

probability laws are implied by previous models.

Model construction is only part of an explanation of the leaving process. Since mathematical models are intended to describe equivalent events, i.e., equivalent individuals leaving equivalent social positions, it is also necessary to identify variables affecting the magnitude of the parameters of a model. In the application of these models to job mobility of Mexican-American men, the variables examined include calendar year, certain fixed attributes of jobs and jobholders, and the jobholder's age, duration in the job, and previous work experiences.

For respondents leaving jobs as operatives, nonfarm laborers, and farm laborers during 1935-1967, educational level and occupation generally affected most the rate of leaving jobs. Job duration was very important; the jobholder's age at entering the job was not. Previous work experiences had some effect but need further study, especially because of their relevance to the validity of the Markov assumption. Other variables were influential in special cases.

The identification of variables affecting the leaving process gave twenty-one sets of data for evaluating probability laws. Probability Law I was satisfactory for four data sets, but predictions for the other seventeen data sets were noticeably improved with one or more of the other probability laws. The probability law derived from a two-stage model of a job consistently gave the best predictions, although improvement was slight. Substantively, the two-stage model leading to this probability law appeared particularly worthy of further investigation.

In previous mobility models the process of individuals

entering new social positions has received limited attention. This study considers simple models of the conditional probability of individuals moving among jobs. Fundamental quantities in the models are the distribution of job vacancies and the attraction of jobs with certain attributes for individuals with certain attributes. Ways of approximating and estimating job vacancies are also considered.

The application of these models to job mobility of Mexican-American men focuses on the impact of different variables on the attraction of different jobs in selected geographical locations. The most significant variables were the geographical location and occupation of the jobs entered and left, and the jobholder's educational level and earlier occupation. Results suggested that the distribution of filled jobs is a rough approximation to the distribution of job vacancies.

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By

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INTRODUCTION

As a person approaches physical and social maturity, he typically begins to engage in activities which are socially denoted as work or labor. In modern societies work is highly differentiated: it is socially significant not only whether or not a person works, but also what kind of work he does (his occupation) and in what social and physical setting he does it (his work situation). Together occupation and work situation identify a person's job.

From time to time a person may change his job;[1] that is, he may change his occupation, his work situation, or both. Occasionally a person may be unemployed, i.e., temporarily between jobs. And eventually everyone's work history ends: each worker either retires or dies while holding a job.

The aim of this research is to develop an improved explanation of movement into and out of jobs for a specified segment of the labor force. While the structure of the explanation should, to a great extent, be applicable to job mobility of members of a labor force in any modern industrialized society, interest in the present investigation focuses on the job mobility of Mexican-American men with a high school education or less who resided in selected Michigan counties during the winter of 1967-1968. Work histories of a sample of 584

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[1] While some individuals have two or more jobs at the same time, this complication is ignored in models considered in the present study.

persons with these characteristics are the data used in this study.

The main stimulus of sociological research on job mobility has been concern for its consequences with regard to both the production and distribution of scarce, valued goods in a society. First of all, work organization and the characteristics of jobholders affect the level and efficiency of the production of goods and services. Productivity will be less than what is technologically possible if job mobility occurs so rapidly that a significant proportion of jobholders are newcomers, or if it occurs so slowly that changes in demands for goods and services cannot be met, or if it fails to match the competencies of individuals with job requirements. Secondly, in modern societies a person's job determines to a great extent both his present life style and his future life chances. Possession of such scarce and generally desired values as wealth, health, education, social prestige, and social power are highly correlated with occupation, although the extent of variation is often considerable within an occupation. Work situation has a secondary but nonnegligible effect: in most occupations in the United States, direct rewards from work tend to be greater in cities than in rural areas, in the Northeast or West than in the South, in a large corporation than in a small company. Thus rates of movement into and out of jobs of particular types indicate the likelihood of improvement, stagnation, or decline in the quality of life for members of the society.

Yet concern for the consequences of job mobility does not necessarily provide a sound basis for understanding the mobility process. Of much more relevance are explanations of other forms of intragenerational social mobility. In the present study social

mobility is used as a generic term indicating movement of individuals among social positions; it includes geographic, occupational, industrial, and social prestige mobility, as well as job mobility.

Previous investigators have been moderately successful in explaining social mobility by viewing it as a stochastic process, i.e., as a process which develops along one or more dimensions, such as time, according to probabilistic laws. Possibilities for improving explanations of this type appear promising and are pursued in this research.

CHAPTER 1

The Scope of the Research

Imagine a system with a finite number of objects and a finite number of positions matched in such a way that each object is associated with ("occupies") at most one position and each position is occupied by at most one object. Not all objects necessarily occupy a position, nor are all positions necessarily filled. If from time to time an object instantaneously changes location according to a probability law, then change in the system, i.e., mobility, is a stochastic process.

A stochastic model of social mobility can be constructed by describing for the system above (1) the objects which move, (2) the positions which the objects may occupy, (3) the points in time when the objects may move, (4) the conditions under which movement occurs, and (5) the probability law which describes the movement of the objects among the position through time. In this chapter I discuss major alternatives for each of these five features and indicate reasons for restricting the present study to models with particular characteristics.

1.1 The objects which move

For the purpose of constructing stochastic models of social mobility there are at least four possible ways of conceptualizing the object which moves: (1) as an individual moving from one social position to another; (2) as a social position moving from one individual to another; (3) as a vacancy moving from one social position to another;

(4) as unattachment moving from one individual to another. Which conceptualization is chosen depends on the object of explanation and the type of data available for testing models.

The first is appropriate when one wants to explain the changing social positions of certain individuals, for example, the Mexican-Americans in the present study. The second is appropriate when one wants to explain the changing composition of the incumbents of certain social positions possessing an existence and identity independent of an occupant, for example, seats in the U.S. Senate or House of Representatives. The third is appropriate when one wants to explain movement in the system generated by sequences of vacant social positions "pulling" individuals out of social positions. This conceptualization has primarily been developed by Harrison C. White (1968, 1969, 1970) and tested by him using data on the movement of clergy among pastorates. The fourth conceptualization is appropriate when one wants to explain movement in the system generated by sequences of unattached individuals "pushing" or "bumping" other individuals out of their social positions, which occurs, for example, when men in unionized factories whose current job has been terminated "bump" less senior men from their jobs (cf. White, 1970).

Since the type of data required to test models constructed on the basis of these different conceptualizations varies, research may be constrained to a particular conceptualization because of limitations on the type of data available. Information on the histories of individuals is required in the case of the first conceptualization and on the histories of social positions in the case of the second. Information for testing models based on the third and fourth

conceptualizations is generally more difficult to obtain as one must be able to identify both the social destination of an individual's predecessor and the social origin of his successor. Consequently histories of a sample of either individuals or social positions do not suffice as data for testing models of either a vacancy or unattachment chain.

Since work histories of a sample of Mexican-American men are both the data and object of explanation in the present study, further discussion is limited to stochastic models in which the moving objects are people.

The population of moving objects in a stochastic model may be homogeneous or heterogeneous. Homogeneity of the population implies that movement among positions in the system occurs according to the same probability law with the same parameters for every member of the population. Perfect homogeneity of the population is a markedly unrealistic assumption in modeling social mobility, and some degree of heterogeneity has generally been recognized, at least implicitly, in empirical work with stochastic models of social mobility.

Assuming a particular probability distribution of the population on parameters of the model, which permits one to formulate an explicit mathematical expression of the stochastic process for the entire population, is one approach to population heterogeneity. However, the most common approach has been to assume that the same probability law holds throughout the population but that values of parameters vary with sex, ethnicity, educational level, or other relevant variables constant throughout the duration of the mobility process. Thus a heterogeneous population is conceived as being composed of subpopulations

that are homogeneous with respect to variables influencing mobility. In the extreme case each individual defines a separate subpopulation, but it then becomes impossible to estimate parameters for a model. One faces the dilemma of identifying a minimal set of variables which disaggregates the total population into relatively homogeneous subpopulations while retaining sufficient individuals in the subpopulations to permit parameters to be estimated.[1]

In the present study I assume that the Mexican-American population examined is heterogeneous and explore both techniques mentioned above for dealing with the problem of population heterogeneity.

1.2 The positions which the objects may occupy

In choosing to construct models of social mobility in which the moving objects are conceptualized as people, one concurrently chooses to conceptualize the positions which they may occupy as social positions. Like the objects which move, the positions which the objects may occupy may be homogeneous or heterogeneous. Heterogeneity of the social positions is virtually always assumed in work with stochastic models of individuals moving among social positions. The total set of heterogeneous social positions is conceived as being composed of subsets of homogeneous social positions. In the extreme case each social position defines a separate subset, but as in the case of extreme population heterogeneity, it then becomes impossible to estimate parameters for a model. One again faces the dilemma of identifying a minimal set of n variables which disaggregates the total set of

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[1] Regression analysis with parameters of a stochastic model as dependent variables has been proposed by James S. Coleman (1970) as one technique for handling this problem.

heterogeneous social positions into relatively homogeneous subsets while retaining enough social positions in each subset to permit parameters to be estimated. The subsets of homogenous social positions form the states in the state space of the stochastic process. The dimension of the state space is n, the minimal number of variables needed to disaggregate the total set of positions into homogeneous subsets. Most stochastic models of social mobility have assumed a unidimensional state space, but this is not assumed a priori in the present research.

Each dimension of the state space may be discrete or continuous. The set of points or elements in a discrete dimension is finite or countably infinite (in one-to-one correspondence with a set of integers); the set of points in a continuous dimension corresponds to an interval on the real line. Furthermore, the set of points on a particular dimension may be treated as a nominal, ordinal, interval, or ratio scale. The first two are usually associated with a discrete dimension and the last two with a continuous dimension. Movement on a dimension can be treated with much more mathematical elegance if one assumes that the set of points on the dimension represents a ratio scale rather than one of the other types. Even the assumption of an ordinal scale allows construction of mathematically more interesting models, e.g., prestige mobility has been modeled as a simple birth and death process (Coleman, 1964; Mayer, n.d.).

But in the present study discussion is restricted to models in which dimensions of the state space are discrete, finite, and form nominal scales. This eliminates models in which ranking or ordering of social positions forms an intrinsic property of the stochastic

process. I impose this limitation on the discussion because I think that adequate bases for ordering social positions, and in particular for ordering jobs, have not yet been devised.

1.3 The points in time when the objects may move

A stochastic process is defined over a set of ordered points in time. The process occurs in discrete time if the set of time points is finite or countably infinite (in one-to-one correspondence with a set of integers). In a discrete time process movement may be assumed to occur, for example, only on the first day of the month or perhaps on a person's birthday. The process occurs in continuous time if the set of time points corresponds to an interval of the real line. In a continuous time process movement may occur at any moment between the lower and upper boundaries of time.

Phenomena that occur continuously in time can be approximated by discrete time models, and vice versa. Often discrete time models are easier to analyze numerically, while continuous time models are more likely to have simple analytical solutions. Most investigators who have viewed social mobility as a stochastic process have used discrete time models; however, the discussion of stochastic processes is limited hereafter to continuous time models. In particular, discrete time models previously proposed by other investigators are discussed in the continuous time form. This reveals the basic mathematical structure of these models much more clearly than the discrete time form so that similarities and differences of the various models are more easily detected.

1.4 The conditions under which movement occurs

(a) Open or closed system

In an open system moving objects enter and leave the state space, and the total number of objects in the system ordinarily fluctuates with time. The number of objects entering or leaving the system may be expressed either as an explicit function of time or as a time-dependent random variable. Models of open systems are appropriate when behavior of the entire system, its overall growth, as well as internal structural changes, is the object of explanation.

In a closed system objects may neither enter nor leave the system. Clearly people do not move forever, but permanent exit from the system, e.g., retirement from the labor force or death, can be handled by including appropriate absorbing states[2] in the state space. Entrance into the system, e.g., birth or entry into the labor force, can be treated by including a state in the state space that cannot be entered. Interim periods between occupation of social positions can be handled by including unattachment, e.g., unemployment, as a state in the state space. Models of closed systems are suitable when behavior of a segment of the population within the overall system is to be explained. As the present research falls within this category, further discussion centers on closed systems.

(b) Dependence or independence of movement

Under the condition of dependence of movement, a transition from one state to another by one person affects the transition probabilities of others in the system. This happens whenever the number of social

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[2] By definition the probability of leaving an absorbing state is zero.

positions available for occupancy is limited. An analogous situation occurs when a large number of people tries to sit in a small number of chairs: when one person sits in one of the chairs, the chances are reduced that one of the persons still standing will find a seat. Dependence of movement is a realistic assumption for models of labor or geographic mobility in an entire social system: not everyone can be employed as a welder, and not everyone can live in San Francisco. Unfortunately, the amount of data required to test such models is formidably large. One must know not only how many positions of each type are filled at any given time, but also how many positions of each type are vacant at any given time.

Under the condition of independence of movement one assumes that the transition from one state to another by one person does not affect the transition probabilities of any other person in the system. The data available for this study necessitate making this assumption. This assumption may not be a bad approximation when one considers social mobility for only a relatively small segment of the total population of the system. Under these circumstances it is unlikely that the individuals under consideration actually compete for the same position. It is not clear to what extent these conditions apply to the Mexican-American men whose work histories provide the data for this research.

Assuming that transitions are independent does not mean that variables affecting the number of vacancies, and thus transition probabilities, cannot be incorporated into a model. For example, Matras (1960, 1961, 1967) included changes in the distribution of occupations in his discrete time models of occupational mobility. Possibilities of this type are explored in Chapter 4.

1.5 The probability law which describes the movement of the objects among the positions through time

The fundamental assumption is that location in the state space, i.e., the social position of an individual in the social system, is a time-dependent random variable, $S(t)$. Let i, j, and k represent typical elements in the state space. One would like to know the probability that an individual will be in state k at time t when he is in state j at an earlier time u. That is, one wants to know:

$$(1.1) \qquad p_{jk}(u,t) \equiv \text{prob}[S(t) = k \mid S(u) = j]$$

for all j and k and $u < t$. Since matrix notation is sometimes convenient, let P(u,t) represent the matrix of transition probabilities:

$$(1.2) \qquad P(u,t) \equiv \{p_{jk}(u,t)\}.$$

Several assumptions follow naturally from our intuitive understanding of a probabilistic process and from the restrictions imposed earlier in this chapter. Clearly we want to assume that the lower and upper limits of transition probabilities are zero and one, respectively:

$$(1.3) \qquad 0 \leq p_{jk}(u,t) \leq 1.$$

Because the present discussion is limited to closed systems, we want to assume that the probability of moving from a state j at time u to <u>some</u> state in the system at time t is exactly one:

$$(1.4) \qquad \sum_{k} p_{jk}(u,t) = 1.$$

In addition it is reasonable to assume that

$$(1.5) \qquad p_{jj}(t,t) = 1$$

and

$$p_{jk}(t,t) = 0 \tag{1.6}$$

for $j \neq k$, or in matrix notation:

$$P(t,t) = I \tag{1.7}$$

where I is the identity matrix (a square matrix with ones on the diagonal and zeroes everywhere else).

An important question remains: what assumptions should be made concerning the relationship between an individual's location in the state space at one time t and his location at some earlier time u? Mathematically the simplest assumption is that the value of $S(t)$ is independent of the value of $S(u)$ for $u < t$:

$$\text{prob}[S(t) = k \mid S(u) = j] = \text{prob}[S(t) = k] \tag{1.8}$$

for all j and k and $u < t$. Under this assumption an individual's present location in the state space gives no clues concerning his location at any future time. Obviously this is an unrealistic assumption for a theory intended to explain social mobility.

A slightly more complex assumption is that an individual's location in the next small interval of time depends on his present location, but not on the path taken to get to this present location. This is the Markov assumption and can be expressed as follows:

$$\text{prob}[S(t) = k \mid S(u) = j] = \text{prob}[S(t) = k \mid S(u) = j, S(v) = i, \ldots] \tag{1.9}$$

for all i, j, and k and for $v < u < t$. It follows from this assumption

that the Chapman-Kolmogorov equation holds:

$$(1.10) \qquad p_{ik}(v,t) = \sum_j p_{ij}(v,u)\, p_{jk}(u,t),$$

or in matrix notation,

$$(1.11) \qquad P(v,t) = P(v,u)\, P(u,t).$$

From a mathematical point of view the Markov assumption is very attractive. The theory of Markov processes has been rather extensively developed and is sufficiently complex that Markov models can approximate actual mobility processes, but not so complicated that sociologists must deal with intractable mathematical problems. Nevertheless, investigators modeling social mobility have complained from time to time that the Markov assumption is unrealistic and inadequate for constructing models of social mobility.

The force of this criticism can be mitigated by using known techniques for transforming non-Markovian processes into Markov processes. Although these techniques have previously been used, they have not been considered in any systematic fashion by those developing stochastic models of social mobility. Three procedures (cf. Cox and Miller, 1965) particularly applicable to the modeling of social mobility are: (a) the inclusion of supplementary variables, (b) the device of stages, and (c) the use of an imbedded Markov process. The first and second are the basis for two techniques used to develop improved descriptions of the process of an individual leaving a social position; these are discussed as Approaches B and C, respectively, in Chapter 2. The third technique, in which a subset of time points are selected so that the resulting process is Markovian, is applied in the overall

strategy of this research whereby the process of leaving a social position and the process of entering a new position are examined separately (one may have a Markovian interpretation even if the other does not), and also in the rationale given in Section 3.1 for conceptualizing a job, rather than some other social position, as a state j.

Prudence demands that the use of these techniques be thoroughly explored before the Markov assumption is discarded. The fact that this exploration has not been completed provides ample justification for limiting the present research to stochastic processes either manifestly Markovian or else open to a Markovian interpretation through some transformation technique.

In most analyses of social mobility as a Markov process, investigation has been restricted to stationary processes, that is, Markov processes whose transition probabilities are constant through time. But as many have recognized, it is unrealistic to assume that the probabilities of moving from one social position to another do not change with time whether one conceptualizes time as an individual's age, his duration in a position, or the date on the calendar. Hence the present research assumes in general that transition probabilities are nonstationary (time-dependent).

Two additional assumptions are needed to develop the mathematical theory of Markov processes. While these assumptions are reasonable, their necessity is perhaps not as intuitively apparent as that of the four assumptions represented by equations (1.3) through (1.6), and (1.10). The first additional assumption (cf. Feller, 1968) is that for every state j, there exists a continuous function $h_j(t)$, $0 \leq h_j(t) < \infty$, such that:

$$(1.12) \qquad \lim_{\Delta t \to 0} \frac{1 - p_{jj}(t,t + \Delta t)}{\Delta t} = h_j(t).$$

In other words $h_j(t)$, which can be interpreted as the instantaneous rate of leaving state j, exists and is a nonnegative, finite, and continuous function everywhere within the time span being considered. The second additional assumption is that for every pair of states j and k, $j \neq k$, there exist transition probabilities $q_{jk}(t)$, in general depending on time, such that:

$$(1.13) \qquad \lim_{\Delta t \to 0} \frac{p_{jk}(t,t + \Delta t)}{\Delta t} = h_j(t)\, q_{jk}(t)$$

with passage to the limit uniform with respect to j for fixed k, and

$$(1.14) \qquad \sum_k q_{jk}(t) = 1$$

$$(1.15) \qquad q_{jj}(t) = 0.$$

The function $q_{jk}(t)$ can be interpreted as a conditional transition probability, i.e., the probability that state k is the destination <u>if</u> state j is left between t and $t + \Delta t$.

It is also useful to define a function $r_{jk}(t)$ such that

$$(1.16) \qquad r_{jk}(t) = h_j(t)\, q_{jk}(t)$$

for $j \neq k$ and

$$(1.17) \qquad r_{jj}(t) = - h_j(t).$$

The function $r_{jk}(t)$ for $j \neq k$ can be interpreted as the instantaneous rate of transition from state j to state k. Note that

$$(1.18) \qquad \sum_{\substack{k \\ k \neq j}} r_{jk}(t) = - r_{jj}(t)$$

which simply means that the rate of loss from state j exactly balances the sum of the rates at which the other k states gain from state j.

Two systems of partial differential equations, called the forward and backward Kolmogorov equations, can be derived from the six assumptions represented by equations (1.3) through (1.6), (1.10), and (1.12) through (1.15) (cf. Feller, 1968). The forward Kolmogorov equation can be written as follows:

$$(1.19) \qquad \frac{\partial p_{ik}(u,t)}{\partial t} = \sum_{j} p_{ij}(u,t)\, r_{jk}(t)$$

or in matrix notation

$$(1.20) \qquad \frac{\partial P(u,t)}{\partial t} = P(u,t)\, R(t)$$

where

$$(1.21) \qquad \frac{\partial P(u,t)}{\partial t} \equiv \left\{\frac{\partial p_{ik}(u,t)}{\partial t}\right\}$$

and

$$(1.22) \qquad R(t) \equiv \{r_{jk}(t)\}.$$

Similarly the backward Kolmogorov equation can be written:

$$(1.23) \qquad \frac{\partial p_{ik}(u,t)}{\partial u} = - \sum_{j} r_{ij}(u)\, p_{jk}(u,t)$$

or in matrix notation

$$\frac{\partial P(u,t)}{\partial u} = - R(u)\, P(u,t). \tag{1.24}$$

The significance of the Kolmogorov equations lies in the fact that, given the assumptions that have been made in this section, they have a unique solution. Usually investigators modeling social mobility have been interested in obtaining P(0,t), the matrix of probabilities of moving from state i at time 0 to state j at time t, when R(t), the matrix of instantaneous transition rates, is postulated to have a specified form. The appropriate equation to use in order to solve for P(0,t) is (1.20), the forward Kolmogorov equation, which becomes a system of ordinary linear differential equations when time u is set equal to zero:

$$\frac{dP(0,t)}{dt} = P(0,t)\, R(t). \tag{1.25}$$

This equation can in turn be used to derive a system of ordinary linear differential equations for the expected number of individuals in given states at a given time t. Let

$$N(t) \equiv \{n_j(t)\} \tag{1.26}$$

be a row vector of the actual number of individuals in each state j at time t,[3] and let

$$\bar{N}(t) \equiv \{\bar{n}_j(t)\} \tag{1.27}$$

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[3] For mathematical convenience $n_j(t)$ is treated as a continuous variable, whereas actual numbers of individuals must quite obviously be integer quantities.

be a row vector of the expected number of individuals in each state j at time t.

We intuitively expect that on the average $p_{ij}(0,t)$ of the $n_i(0)$ persons in state i at time 0 are in state j at time t. Hence we write:

$$\bar{N}(t) = N(0)\, P(0,t). \tag{1.28}$$

Differentiating this equation with respect to time t yields

$$\frac{d\bar{N}(t)}{dt} = N(0)\, \frac{dP(0,t)}{dt}. \tag{1.29}$$

Substituting according to equation (1.25) and then applying equation (1.28), we obtain:

$$\frac{d\bar{N}(t)}{dt} = \bar{N}(t)\, R(t). \tag{1.30}$$

This equation is equivalent to

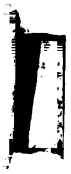
$$\frac{d\bar{n}_j(t)}{dt} = \sum_i \bar{n}_i(t)\, r_{ij}(t) \tag{1.31}$$

or alternatively

$$\frac{d\bar{n}_j(t)}{dt} = -\bar{n}_j(t)\, h_j(t) + \sum_{\substack{i \\ i \neq j}} \bar{n}_i(t)\, h_i(t)\, q_{ij}(t), \tag{1.32}$$

which simply states that the rate of change in the expected number of individuals in state j equals the rate of change in the expected number leaving state j plus the sum of the rates of change in the expected number entering state j from each of the other i states.

Solving a system of differential equations -- either equation (1.25) for the matrix of transition probabilities, P(0,t), or equation



(1.30) for the vector of the expected number of individuals in each state, $\overline{N}(t)$ -- is mathematically difficult unless the matrix of the instantaneous rates of transition among the states, R(t), has a simple form. Yet it has been necessary to rely on this approach in most studies of social mobility because available data has consisted of information on the states occupied by individuals at discrete points in time, rather than information on the exact sequence of states occupied by each individual and the length of time spent in each state. But since continuous time work histories are available in this study, I take a different tack which is derived from the probability theory developed above but does not require solving a system of differential equations. The essence of this tactic is to examine the mobility process on a more fundamental level -- namely, to study separately the process of individuals leaving a social position and the process of individuals entering a new social position, given that they are leaving some other social position.[4] The former is examined in Chapters 2 and 3 and the latter in Chapter 4.

[4] After this research began, I learned that Morrison (1970) advocates essentially the same strategy for developing models of migration.

CHAPTER 2

The Process of Individuals Leaving a Social Position: A Review of Approaches, Models, and Probability Laws

A stochastic model of individuals leaving a social position consists of not only the probability law describing the leaving process but also the set of assumptions used to derive the probability law. This is important because a particular probability law can often be derived from more than one set of assumptions. In such cases testing a model includes, but is not synonymous with, testing a particular probability law. While previous investigators have proposed and tested seven different probability laws intended to describe the process of individuals leaving a social position,[1] they have, properly speaking, proposed somewhat more than seven models because some probability laws were derived from more than one set of assumptions.

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[1] Previous investigators (Rice, Hill, and Trist, 1950; Mayer, 1968) have proposed and tested two other mathematical formulations intended to describe the process of individuals leaving a social position. I am disregarding these because neither formulation, as originally proposed, satisfies the assumption that $0 \leq h_j(t) < \infty$. In the Rice, Hill, and Trist formulation, the expected density of individuals leaving state j is a hyperbolic function of duration t,

$$\bar{f}_j(t) = a\, t^{-b}$$

which implies that $h_j(t) \to \infty$ as $t \to 0^+$. In the Mayer formulation

$$h_j(t) = a\,(1 - bt)\exp[-bt]$$

which is less than zero for $t > 1/b$. Both proposals can be made to fit the restrictions on $h_j(t)$ by suitable limitations on the time span under consideration. In view of the atheoretical basis of both proposals, this task does not presently seem worthwhile.

The seemingly natural assumptions of stationary (time-independence) and population homogeneity lead to the first probability law discussed below, which I have designated Probability Law I. Yet observations on individuals leaving several different types of social positions have deviated consistently from predictions based on this probability law. In order to develop an improved description of the process of individuals leaving a social position, previous investigators have used three sets of general assumptions or approaches; the presentation of these three approaches follows my discussion of Probability Law I. This chapter then concludes with a review and analysis of the six probability laws that have been derived from models constructed through the use of these three approaches. With one exception the order of discussion of these probability laws follows the chronology of their original published proposal.

In the present chapter I do not undertake to discuss or resolve several important issues relevant to an explanation of social mobility. These include establishing correspondences between the theoretical construct "state j" and observable social positions and between the theoretical construct "time t" and observable measures of time, as well as identifying equivalent individuals (i.e., homogeneous subpopulations) and equivalent social positions. In discussing the work of previous investigators in this chapter I report without critical comment their decisions concerning these issues. My own thoughts on these problems are given in Chapter 3.

In order to understand and compare models of individuals leaving a social position, it is necessary to develop further the mathematical theory presented in Chapter 1. The starting point is equation (1.32):

$$(2.1) \qquad \frac{d\bar{n}_j(t)}{dt} = -\bar{n}_j(t)\, h_j(t) + \sum_{\substack{i \\ i \neq j}} \bar{n}_i(t)\, h_i(t)\, q_{ij}(t).$$

If we ignore those who enter state j after some point in time arbitrarily defined as time 0, this equation becomes:

$$(2.2) \qquad \frac{d\bar{n}_j(t)}{dt} = -\bar{n}_j(t)\, h_j(t).$$

The solution of this differential equation is easily found. Separating the variables, we obtain

$$(2.3) \qquad \frac{d\bar{n}_j(t)}{\bar{n}_j(t)} = -h_j(t)\, dt,$$

and after integrating both sides,

$$(2.4) \qquad \ln \bar{n}_j(t) - \ln \bar{n}_j(0) = -\int_0^t h_j(u)\, du.$$

Let $\bar{G}_j(t)$ be the expected proportion remaining in state j at time t. The preceding equation implies that

$$(2.5) \qquad \bar{G}_j(t) = \frac{\bar{n}_j(t)}{n_j(0)} = \exp\left[-\int_0^t h_j(u)\, du\right].$$

In addition, let $\bar{F}_j(t)$ be the proportion expected to have left state j at time t, that is

$$(2.6) \qquad \bar{F}_j(t) = 1 - \bar{G}_j(t),$$

and therefore applying equation (2.5),

$$(2.7) \qquad \bar{F}_j(t) = 1 - \exp\left[-\int_0^t h_j(u)\, du\right].$$

Differentiating $\bar{F}_j(t)$ with respect to time t, we obtain:

$$(2.8) \qquad \bar{f}_j(t) = \frac{d\bar{F}_j(t)}{dt} = h_j(t) \exp\left[- \int_0^t h_j(u)\, du\right],$$

where $\bar{f}_j(t)$ is the probability density function for the expected number of leavers at time t. Equations (2.5) and (2.8) together imply that

$$(2.9) \qquad h_j(t) = \frac{\bar{f}_j(t)}{\bar{G}_j(t)} .$$

Note that $h_j(t)$, the instantaneous rate of leaving state j, uniquely determines $\bar{G}_j(t)$, $\bar{F}_j(t)$, and $\bar{f}_j(t)$. In other words, a probability law describing the process of individuals leaving a social position may be specified by postulating $h_j(t)$, $\bar{G}_j(t)$, $\bar{F}_j(t)$, or $\bar{f}_j(t)$. In order to ensure clarity of presentation and to facilitate comparisons, I indicate $h_j(t)$, $\bar{G}_j(t)$, and $\bar{f}_j(t)$ for each probability law discussed below. I omit $\bar{F}_j(t)$ because it can be obtained very simply from $\bar{G}_j(t)$ using equation (2.6). In the equations for these functions Greek letters represent parameters of the probability law. These parameters are assumed to be fixed for individuals in a given state j who are homogeneous on all variables affecting the process of their leaving state j.

2.1 Probability Law I

The mathematical equations defining Probability Law I are:

$$(2.10) \qquad h_j(t) = \kappa$$

$$(2.11) \qquad \bar{G}_j(t) = \exp[- \kappa t]$$

$$(2.12) \qquad \bar{f}_j(t) = \kappa \exp[- \kappa t]$$

where $\kappa \geq 0$ and time $t \geq 0$.

Probability Law I arises from the assumption that members of a

homogeneous population (which presumably has been identified) leave a given state j at a fixed rate κ as given by equation (2.10). This assumption seems natural to us because we fundamentally assume that the probability of a well-defined event (e.g., leaving state j) does not change from moment to moment. If evidence supports the fact that the probability of an event changes with time, then we ordinarily doubt that the event is "well-defined," i.e., that instances of the same phenomena have been observed. Consequently Probability Law I, in spite of its simplicity, serves as the standard basis of comparison as well as the foundation from which other models are constructed.

The stationary Markov process, a special case of Probability Law I often discussed as a model of social mobility, requires the additional assumption that $q_{jk}(t)$, the conditional probability of a move from state j to state k, is independent of time for all states j and k. With equation (1.16) this implies that

$$r_{jk}(t) = r_{jk} \tag{2.13}$$

for all states j and k. In other words, the matrix of instantaneous transition rates, R(t), is independent of time:

$$R(t) = R. \tag{2.14}$$

Given these assumptions it can readily be shown that equation (1.25) has the solution

$$P(0,t) = \exp[Rt] \tag{2.15}$$

and that equation (1.30) has the solution

$$\overline{N}(t) = N(0) \exp[Rt] \tag{2.16}$$

where by definition

$$\exp[Rt] \equiv \sum_{z=0}^{\infty} \frac{(Rt)^z}{z!} \tag{2.17}$$

and

$$R^0 \equiv I. \tag{2.18}$$

If the total number of states in the system is finite, as I assumed in Section 1.2, the above expressions for $P(0,t)$ and $\overline{N}(t)$ converge to a limit.

Blumen, Kogan, and McCarthy (1955) tested the discrete time version of equation (2.15) using records of the Bureau of Old Age and Survivor Insurance to determine the industry in which a sample of workers were employed during twelve consecutive quarters. They used the matrix of the proportion of transitions between industries in one quarter to predict the matrix of the proportion of transitions between industries in four and eight quarters for both males and females in three different age groups. As the length of time of the prediction increased, the predicted values increasingly differed from the observed values. In particular, the authors found that the model overestimated the number of workers who had changed their industry after a long period of time. Further investigation showed that workers with a long period of continuous employment in an industry were more likely to remain in the same industry for one more quarter than were workers with a short period of continuous employment in the same industry. The magnitude of this effect differed among industries. Since equation (1.12) implies that

$$p_{jj}(t,t + \Delta t) \sim 1 - h_j(t)\,\Delta t \tag{2.19}$$

where $p_{jj}(t,t + \Delta t)$ is the probability of remaining in state j at time

t for an additional small interval of time Δt, the observations of these investigators are consistent with the conjecture that $h_j(t)$, the instantaneous rate of leaving state j, is a declining function of time t rather than independent of time as in Probability Law I.

Probability Law I has also been tested with data on labor mobility without the added assumption that $q_{jk}(t)$, the conditional probability of a move from state j to state k, is independent of time for all states. Silcock (1954) used data on the distribution of the length of employment of workers who had left two British factories to estimate parameter κ for Probability Law I. When he used his estimate of κ to predict the distribution of the length of employment of the workers, he found large discrepancies between the actual and predicted distributions. The predicted number of leavers in an interval Δt, approximately $n_j(0)\ \bar{f}_j(t)\ \Delta t$, was too low for short durations of employment and too high for long durations. In order to achieve a better prediction, $h_j(t)$, the instantaneous rate of leaving state j, needs to be larger than the estimate of κ for short durations and smaller than the estimate of κ for large durations. In other words, Silcock's results also suggest that $h_j(t)$ declines with time.

Data obtained by Hedberg (1961) on the completed length of employment of male workers hired during 1949-1952 in sixteen Swedish factories also provide a test of Probability Law I. Hedberg plotted the logarithm of the observed proportion remaining in a factory versus duration t for seven age categories. Equation (2.5) implies that

$$\ln \bar{G}_j(t) = -\int_0^t h_j(u)\, du \tag{2.20}$$

so that for Probability Law I,

$$\ln \bar{G}_j(t) = -\kappa t. \tag{2.21}$$

If Probability Law I is valid, then a plot of the logarithm of the observed proportion remaining in state j at time t versus t should be linear with a slope of $-\kappa$. However the plots with Hedberg's data are decidedly nonlinear, closely resembling a negative exponential curve. This led Hedberg to suggest that

$$h_j(t) = \omega \exp[-\Phi t] + \xi. \tag{2.22}$$

This is discussed below as Probability Law IV.

Probability Law I can also be tested by using data to calculate the probability of leaving state j during a small interval Δt given that duration t has already been spent in the state. This probability is $(1 - p_{jj}(t, t + \Delta t))$ and approximately equals $h_j(t)\,\Delta t$ according to equation (2.19). Consequently, if Probability Law I holds, a plot of the duration-specific rate of leaving state j versus duration t should be approximately equal to $\kappa\,\Delta t$ for all values of t, i.e., a straight line with a slope of zero.

At least three studies of geographic mobility have reported their findings in terms of duration-specific rates of individuals leaving a geographical area, $(1 - p_{jj}(t, t + \Delta t))$. Myers, McGinnis, and Masnick (1967), using attendance records for three different years of senior high school students in Seattle, Morrison (1967), using data on four different age categories of male residents of Amsterdam economic-geographic areas, and Land (1969), using data on four different age categories of male residents of municipios in Monterrey, Mexico, found that the probabilities of migrating during the forthcoming year tended to decrease as duration of residence increased. Morrison recorded one interesting exception: for the 18-24 year old age category, the semi-annual probabilities of migrating increased gradually for the first

two years before beginning to decline rather sharply. These findings do not support Probability Law I. Instead they indicate that $h_j(t)$, the instantaneous rate of leaving state j, declines with increases in duration, or possibly increases with short durations before beginning to decline with longer durations.

2.2 Approach A: The assumption of nonstationarity

From a mathematical point of view Approach A is the simplest of the three sets of general assumptions previously used to construct models of individuals leaving a social position whose predictions improve upon those of Probability Law I. The instantaneous rate of leaving a state j, $h_j(t)$, is assumed to be a particular nonstationary (time-dependent) function possessing certain desired characteristics rather than a time-independent constant as in Probability Law I. In the applications of Approach A to date, the only reason for proposing one probability law rather than another has been a resemblance between selected features of data and some standard mathematical function. Thus Approach A has been used solely as a curve-fitting technique. In spite of its lack of substantive theoretical support, this approach has still been useful in suggesting the minimal mathematical properties that a substantive model should possess.

2.3 Approach B: The assumption of population heterogeneity

Three main assumptions underlie Approach B: (1) There exists a probability density function $c_j(y,0)$ which describes the distribution of individuals in state j at time 0 on some continuous variable y with range (a,b). This implies that the density of individuals in state j with position y at time 0, $m_j(y,0)$, can be written as follows:

(2.23) $$m_j(y,0) = n_j(0)\, c_j(y,0),$$

where again $n_j(0)$ is the number in state j at time 0. (2) The instantaneous rate of leaving state j is a function of both time t and position y, $h_j(y,t)$. (3) An individual's position on variable y does not change during his duration in state j. Hence we can write the following equation, analogous to equation (2.2), for the density of the expected number of individuals in state j with position y at time t, $\bar{m}_j(y,t)$:

(2.24) $$\frac{d\bar{m}_j(y,t)}{dt} = -\bar{m}_j(y,t)\, h_j(y,t).$$

Through steps exactly parallel to those used to solve equation (2.2), we can obtain the solution to this equation:

(2.25) $$\frac{\bar{m}_j(y,t)}{m_j(y,0)} = \exp\left[-\int_0^t h_j(y,u)\, du\right].$$

Substituting according to equation (2.23) and rearranging, we obtain:

(2.26) $$\bar{m}_j(y,t) = n_j(0)\, c_j(y,0) \exp\left[-\int_0^t h_j(y,u)\, du\right].$$

Since

(2.27) $$\bar{n}_j(t) = \int_a^b \bar{m}_j(y,t)\, dy,$$

integrating both sides of equation (2.26) over y from a to b and then rearranging the results produces the following expression for $\bar{G}_j(t)$, the expected proportion remaining in state j at time t:

(2.28) $$\bar{G}_j(t) = \frac{\bar{n}_j(t)}{n_j(0)} = \int_a^b c_j(y,0) \exp\left[-\int_0^t h_j(y,u)\, du\right]dy.$$

If the variable y is discrete rather than continuous, we obtain an analogous equation:

$$(2.29) \qquad \bar{G}_j(t) = \frac{\bar{n}_j(t)}{n_j(0)} = \sum_{y=a}^{b} c_j(y,0) \exp\left[- \int_0^t h_j(y,u)\, du \right].$$

2.4 Approach C: The assumption of stages within state j

This approach assumes that a state j is composed of some finite number of stages and that movement among these stages and out of state j is a Markov process. Let state j be composed of d stages, and let those who leave state j enter an absorbing state L. Assuming that L is an absorbing state means that the instantaneous rate of leaving L, $h_L(t)$, is zero:

$$(2.30) \qquad h_L(t) = 0$$

which implies that the instantaneous rate of transition from L to any stage z in state j, r_{Lz}, is also zero:

$$(2.31) \qquad r_{Lz} = 0.$$

Assuming that movement among stages within state j and to L is a Markov process implies that the instantaneous rate of leaving any stage z in state j, $h_j(z,t)$, is a constant μ_z:

$$(2.32) \qquad h_j(z,t) = \mu_z,$$

where $\mu_z \geq 0$ and $t \geq 0$, and also that the conditional probability of transitions from stage z to L or to another stage w in state j, $w \neq z$, are time-independent constants, q_{zL} and q_{zw}, respectively, with

$$(2.33) \qquad q_{zL} = \sum_{\substack{w=1 \\ w \neq z}}^{d} q_{zw} = 1.$$

This implies that R(t), the matrix of instantaneous rates of transition among stages within state j, is independent of time:

$$R(t) = R \equiv \{r_{zw}\} \tag{2.34}$$

where

$$r_{zz} = -\mu_z \tag{2.35}$$

and

$$r_{zw} = \mu_z q_{zw}. \tag{2.36}$$

If λ_z, the eigenvalues of the matrix R, are distinct negative constants or zero, then the equations defining the probability law describing the process of individuals leaving state j can be written as follows:

$$h_j(t) = \frac{-\sum_{z=1}^{d} \beta_z \lambda_z \exp[\lambda_z t]}{\sum_{z=1}^{d} \beta_z \exp[\lambda_z t]} \tag{2.37}$$

$$\overline{G}_j(t) = \sum_{z=1}^{d} \beta_z \exp[\lambda_z t] \tag{2.38}$$

$$\overline{f}_j(t) = -\sum_{z=1}^{d} \beta_z \lambda_z \exp[\lambda_z t] \tag{2.39}$$

where

$$\beta_z = -b_{Lz} \tag{2.40}$$

and the value of b_{Lz} is found by solving the following simultaneous equations:

$$n_L(0) = 0 = 1 + \sum_{w=1}^{d} b_{Lw} \tag{2.41}$$

$$n_z(0) = b_{zL} + \sum_{w=1}^{d} b_{zw} \tag{2.42}$$

$$(2.43) \qquad \sum_{w=1}^{d} r_{wx} b_{wz} = \lambda_z b_{xz}$$

$$(2.44) \qquad \sum_{w=1}^{d} r_{wx} b_{wL} = 0$$

with z taking the values one to d and x taking the values one to d and L.

Models constructed through Approach C can be divided into three subtypes: (a) models with all stages in series, (b) models with all stages in parallel, and (c) models with stages both in parallel and in series. The parameters of the probability law describing the process of leaving state j have somewhat different characteristics for the three subtypes.

Probability laws derived from models of subtype (a), which have all stages in series (cf. Figure 2.1), are instances of the general

stage 1 ⟶ stage 2 ⟶ . . . . ⟶ stage d ⟶ L

Figure 2.1 General structure of models with all stages in series

Erlangian distribution, for which the parameter λ_z equals minus the instantaneous rate of leaving stage z,

$$(2.45) \qquad \lambda_z = - \mu_z$$

for z = 1, 2, . . ., d, and the parameters β_z are as follows:

$$(2.46) \qquad \beta_z = \sum_{\substack{w=1 \\ w \neq z}}^{d} \mu_w / (\mu_w - \mu_z).$$

If the instantaneous rate of leaving each stage in state j is the same,

$$(2.47) \qquad \mu_z = \mu$$

for z = 1, 2, . . ., d, then the probability law is known as the special Erlangian distribution and the expression for $\bar{f}_j(t)$ becomes:

$$(2.48) \qquad \bar{f}_j(t) = \mu^d \, t^{d-1} \exp[-\mu t] / (d-1)! \; .$$

If we abandon the notion of distinct stages and permit d to take on any positive real value, then equation (2.48) becomes the probability density function of the gamma distribution, which we can consider a generalization of the special Erlangian distribution. While a simple analytic expression for $h_j(t)$, the instantaneous rate of leaving state j, cannot be written for either the special Erlangian or gamma distribution, it can be shown that $h_j(t)$ peaks at some time t greater than zero for d greater than one. As I indicated in the discussion of Probability Law I in Section 2.1, this may be a desirable property for a model of social mobility to have. To my knowledge no model of subtype (a) has yet been tested using data on social mobility.

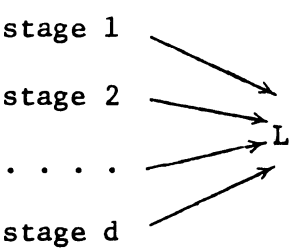

Figure 2.2 General structure of models with all stages in parallel

For probability laws derived from models of subtype (b), which have all stages in parallel (cf. Figure 2.2),

$$(2.49) \qquad \lambda_z = -\mu_z$$

and the parameters β_z are in the range (0,1) for z = 1, 2, . . ., d. We can think of a probability distribution existing for the set $\{\beta_z\}$ with β_z equal to the probability that an individual enters stage z.

Models of subtype (b) of Approach C closely resemble models constructed through Approach B. In fact, these two types of models have only one significant difference: the variable y in Approach B ordinarily refers to attributes of individuals, whereas the variable z in Approach C, subtype (b), refers to attributes of positions. If variable z is substituted for variable y, then equations (2.28) and (2.29) can be used to define the probability law for a model with all stages in parallel.

No general statements can be made about the parameters β_z and λ_z of probability laws derived from models of subtype (c) of Approach C, which have stages both in parallel and in series. All previously proposed models of individuals leaving a social position constructed through the use of Approach C have been of this subtype. These models have assumed that everyone in state j begins in the same initial stage, sometimes called the undecided stage, and eventually leaves this stage to become more or less committed to state j. In other words, unlike models of subtype (b), these models have postulated that at time 0 all positions in state j are truly equivalent and occupied by truly equivalent individuals.

2.5 Probability Law II

The mathematical equations defining Probability Law II are:

$$(2.50) \qquad h_j(t) = \delta/(\Theta + t)$$

$$(2.51) \qquad \overline{G}_j(t) = \Theta/(\Theta + t)^{\delta}$$

$$(2.52) \qquad \overline{f}_j(t) = (\delta/\Theta)[\Theta/(\Theta + t)]^{\delta+1}$$

where $\delta > 0$, $\Theta > 0$, and $t \geq 0$.

Silcock (1954) proposed Probability Law II after finding large discrepancies between the actual distribution of the length of employment of workers who had left two British factories and the distribution predicted by Probability Law I. He postulated that individuals vary in their proneness to leave, or in terms of the mathematical theory developed in the presentation of Approach B in Section 2.3, that

$$(2.53) \qquad h_j(y,t) = y,$$

and that initially they are gamma-distributed on y,

$$(2.54) \qquad c_j(y,0) = \Theta^{\delta} y^{\delta-1} \exp[-\Theta y]/(\delta - 1)!$$

where $y \geq 0$ and duration $t \geq 0$. Substituting these equations into equation (2.28) and simplifying, we obtain equation (2.51).

Silcock postulated that individuals are initially gamma-distributed on y because of the usefulness of this assumption in accident theory and not because of any substantive sociological reasons. He did not mention any concept with which the variable y could be associated but remarked that "whereas accident proneness, if it exists, would seem to be a characteristic of the individual, the rate of wastage [i.e., the instantaneous rate of leaving] depends on both employer and employee and might be expected to change as the individual moves from one job to the next" (Silcock, 1954: 435). This implies a hybrid of Approach B, the assumption of population heterogeneity, and Approach C, subtype (b), the assumption of parallel stages within state j.

Probability Law II can also be constructed through Approach A, the assumption of nonstationarity. In this case, for all members of a homogeneous population in state j the instantaneous rate of leaving decreases as time t increases as given in equation (2.50). The

instantaneous rate of leaving state j, $h_j(t)$, is δ/Θ at time 0 and declines monotonically, asymptotically approaching zero as time t approaches infinity.

Silcock used data on the distribution of the length of employment of workers who had left several British factories to estimate the parameters for Probability Law II. In each case he then used these parameter estimates to calculate the expected distribution of the length of employment, $n_j(0)\ \bar{f}_j(t)\ \Delta t$. On the basis of a χ^2 test of the goodness of fit, Probability Law II could not be ruled out; however, the results were not incontrovertible.

2.6 Probability Law III

The mathematical equations defining Probability Law III are:

$$h_j(t) = \bar{f}_j(t) \ / \ \bar{G}_j(t) \tag{2.55}$$

$$\bar{G}_j(t) = 1 - \int_0^t \bar{f}_j(u)\ du \tag{2.56}$$

$$\bar{f}_j(t) = (\exp[\ -\ (\ln t - \zeta)^2 \ / \ 2\sigma^2]) \ / \ \sqrt{2\pi}\ \sigma t \tag{2.57}$$

where $\sigma > 0$ and time $t \geq 0$. Equation (2.57) is the probability density function of the lognormal probability distribution.

Lane and Andrew (1955) originally proposed this probability law after examining the distributions of the length of employment of workers who had left branches of a British steel factory. They postulated (1955: 297) "that the probability of an employee's leaving is strongly dependent upon his length of service," an assumption of duration-dependent nonstationarity. However, the authors suggested no substantive reasons for selecting the lognormal probability law. Furthermore, their sole test of the probability law was to observe that plots on

logarithmic probability paper of the observed proportion remaining in a branch of the factory versus duration t appeared to be straight lines.[2]

An attractive feature of Probability Law III is that $h_j(t)$, the instantaneous rate of leaving state j, increases to a maximum at some time t greater than zero and then decreases to zero as time t approaches infinity. As I mentioned in the discussion of Probability Law I in Section 2.1, for Morrison's (1967) data on 18-24 year olds the semiannual probability of migrating gradually increased as duration of residence increased to two years and then declined with further increases in duration of residence. Likewise Lane and Andrew's data indicate that the probability of leaving the factory was very low during the first week of employment, then gradually increased during the first month or two of employment, and finally declined with further increases in duration of employment. In the discussion following Lane and Andrew's paper (1955), Spratling reported that the probability of quitting work during the next month peaked at three months in data on station porters. Probability Law III is one of the few previously proposed probability laws that is consistent with observations indicating that $h_j(t)$ peaks at some time t greater than zero.

However the substantive interpretations which have been proposed for Probability Law III seem less than satisfactory. In a brief comment on Lane and Andrew's paper (1955: 318), Aitchison, coauthor with Brown of The Lognormal Distribution (1957), offered the following

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[2] Logarithmic probability paper has the ordinate scale (duration in this instance) graduated logarithmically and the abscissa scale (in this case the proportion remaining in a branch of the factory) graduated as the equivalent normal deviates.

interpretation of Probability Law III:

> . . . suppose that Kapteyn's law of proportionate effect holds, namely, that the chance of an employee with x years service remaining in service for another y years depends only on the ratio y/x; such a system if allowed to operate freely would generate a stable lognormal population of lengths of service . . .

I understand this to mean that $p_{jj}(x, x + y)$ depends only on y/x, a conjecture of duration-dependent nonstationarity deserving consideration. However my attempts to derive Probability Law III from a formal expression of this conjecture have not yet been successful.

On the other hand, in a modification of Aitchison's interpretation, Bartholomew (1967) has demonstrated that a lognormal distribution of lengths of jobs arises under the following assumption: (a) let t_x, the length of an individual's x^{th} job, be a random multiple of the length of his previous job,

$$t_x = u_x t_{x-1} \tag{2.58}$$

where $x = 2, 3, \ldots, \infty$ and $\{u_2, u_3, \ldots\}$ is a sequence of random variables with a known joint probability distribution, and (b) let the central limit theorem hold for the summation of $\ln u_x$, $x = 2, 3, \ldots, \infty$. It then follows that the logarithm of the x^{th} job, $\ln t_x$, approaches a normal distribution as x approaches infinity. To Bartholomew (1967: 130) this suggested "that if particular care is taken to ensure satisfaction in a person's first job then their subsequent rate of turnover will be reduced." Note that the interpretation proposed by Bartholomew is non-Markovian (length of present job depends on previous experience) and arises from an assumption of population heterogeneity (Approach B) rather than nonstationarity (Approach A).

Although mathematically correct, Bartholomew's interpretation of

Probability Law III seems unsatisfactory from a substantive point of view. Bartholomew does not explain why the length of an individual's second (third, fourth, etc.) job should be a random multiple of the length of his previous job, and the prima facie evidence for this postulate is weak. For example, this assumption implies that if the length of the first job was forty years for one man (as occurred in my sample) and six months for another, then the probability that the second job lasts more than ten years is greater for the first person than the second, an implausible conclusion given that a working career rarely lasts more than fifty years. Even if this postulate is correct, it does not mean that Probability Law III describes the process of leaving the x^{th} job when x is small, and in particular, when x equals one. While Probability Law III may have a desirable feature in $h_j(t)$, the instantaneous rate of leaving state j, peaking at some time t greater than zero, further work on the underlying model from which it is derived is needed.

2.7 Probability Law IV

The mathematical equations defining Probability Law IV are:

$$h_j(t) = \omega \exp[- \Phi t] + \xi \tag{2.59}$$

$$\overline{G}_j(t) = \exp[- \xi t - \omega(1 - \exp[- \Phi t])/\Phi] \tag{2.60}$$

$$\overline{f}_j(t) = (\omega \exp[- \Phi t] + \xi) \exp[- \xi t - \omega(1 - \exp[- \Phi t])/\Phi] \tag{2.61}$$

where $\omega > 0$, $\Phi > 0$, $\xi \geq 0$, and time $t \geq 0$.

Note that as time t increases, the instantaneous rate of leaving state j, $h_j(t)$, asymptotically approaches ξ. If ξ equals zero, then the expected proportion remaining in state j after infinite time is nonzero:

$$(2.62) \qquad \lim_{t\to\infty} \bar{G}_j(t) = \exp[-\omega/\Phi]$$

Contrarily, if ξ is greater than zero, the expected proportion remaining in state j after infinite time is zero. Given that everyone eventually dies, the latter is a more realistic assumption for a model of individuals leaving a social position.

Since the instantaneous rate of leaving state j, $h_j(t)$, must always be nonnegative (cf. equation (1.12)) and appears to decline with time on the basis of most previous observations, one of the simplest postulates is that its proportionate rate of decrease is constant:

$$(2.63) \qquad \frac{dh_j(t)}{dt} = -\Phi h_j(t).$$

The solution to this differential equation is equation (2.59) with parameter ξ equal to zero. Equation (2.59) is obtained exactly by assuming that

$$(2.64) \qquad \frac{dh_j(t)}{dt} = -\Phi[h_j(t) - \xi].$$

Probability Law IV can be constructed through the assumption of population heterogeneity (Approach B) or of stages within state j (Approach C, subtype (b)) as well as through the assumption of nonstationarity (Approach A) as described in the preceding paragraph. In this case we postulate that there exists a variable y (an attribute of individuals in Approach B or of social positions in Approach C, subtype (b)) such that

$$(2.65) \qquad h_j(y,t) = \Phi y + \xi,$$

where $y = 0, 1, 2, \ldots, \infty$ and $t \geq 0$, and that the initial distribution on y is a Poisson distribution with parameter ω/Φ,

$$(2.66) \qquad c_j(y,0) = \exp[-\omega/\Phi](\omega/\Phi)^y / y! \ .$$

Substituting equations (2.65) and (2.66) into equation (2.29) and simplifying yields equation (2.60) of Probability Law IV.

Insofar as studies of social mobility are concerned, Hedberg (1961) appears to be the first to have proposed Probability Law IV.[3] Of the researchers who have discussed this probability law with reference to social mobility, only Hedberg postulated that the parameter ξ is greater than zero. While the analysis of his apparently excellent data on the length of employment of workers in sixteen Swedish factories led Hedberg to propose that the instantaneous rate of leaving declines with duration t as given by equation (2.59), he unfortunately did not choose to use these data to estimate the parameters of Probability Law IV or to test the probability law in any way.

Mayer (1968), the only person actually to test a version of Probability Law IV with data on social mobility, postulated that the instantaneous rate of leaving declines with age t as given by equation (2.59) with parameter ξ zero. This test is not conclusive because of the a priori assumption that ξ is zero and because of the nature of Mayer's data, which consisted of occupational status scores of the first job and the job in March of 1962 for 20,700 U.S. males aged 20 to 64 years. Because Mayer had data on only two points in a man's career, he did not know when an individual left any particular status and therefore could not look directly at the process of individuals leaving a single state j. Instead he investigated the overall mobility

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[3] Probability Law IV has a much lengthier history in the study of human mortality than in the study of human mobility (cf. Gompertz, 1825, and Makeham, 1860, as cited by Chiang, 1968).

process, solving equation (1.25) for P(0,t). In order to solve this equation he assumed that the parameter Φ in equation (2.59) is the same for all occupational statuses and that $q_{jk}(t)$, the conditional probability of moving from state j to state k, is independent of time for all states j and k. Furthermore, he found it necessary to construct a synthetic cohort, i.e., to treat data on different age groups gathered at one point in calendar time as observations on a single birth cohort at different points in its life history. Using a synthetic cohort presents no problems if the structure of the mobility process remained relatively constant between 1916 (when the 64 year old men in his sample presumably entered the labor force) and 1962; however, the validity of this presupposition is highly dubious. Mayer rated the predictive ability of his version of Probability Law IV as "not terribly impressive," but given the limitations of this test, Probability Law IV should not be eliminated from further consideration.

McGinnis's Axiom of Cumulative Inertia (1968: 716), which states that "the probability of remaining in any state of nature increases as a strict monotonic function of duration of prior residence in that state," is an assumption of duration-dependent nonstationarity and therefore one form of Approach A. This axiom has been incorporated by McGinnis and his coworkers into what has been named the Cornell Mobility Model. In his discussion of the Cornell Mobility Model, McGinnis (1968) defined the mobility process with two matrices, termed by him $R \equiv \{r_{ij}\}$ and ${}_dS \equiv \{{}_ds_{ii}\}$. The conditional probability of moving from state j to state k, $q_{jk}(t)$,[4] is equivalent to r_{ij} in McGinnis's

[4]My own notation is used unless otherwise indicated.

notation; this is not pertinent to the present discussion of models of individuals leaving a social position. However, what McGinnis termed ${}_{d}s_{ii}$ is equivalent to the probability of remaining in a state j at time t for the next interval of time Δt, $p_{jj}(t, t + \Delta t)$, which is directly related by equation (2.19) to $h_j(t)$, the instantaneous rate of leaving state j.

In particular, McGinnis reported that computer simulation experiments had been carried out under the assumption that "with each increment of time, the probability of staying is increased by a fixed fraction, $1/\alpha$, of the remaining range, $I - {}_{d-1}S$" (McGinnis, 1968: 719). For a given state this implies (in McGinnis's notation) that

$$(2.67) \qquad {}_{d}s_{ii} = 1 - (1 - 1/\alpha)^{d-1} (1 - {}_{1}s_{ii})$$

for $\alpha > 1$. In my notation this implies that

$$(2.68) \qquad h_j(t)\, \Delta t \sim (1 - 1/\alpha)^{t} (1 - p_{jj}(0, 0 + \Delta t)).$$

If McGinnis's parameter α is large, then

$$(2.69) \qquad (1 - 1/\alpha)^{t} = [(1 - 1/\alpha)^{-\alpha}]^{-t/\alpha} \sim \exp[-t/\alpha],^{5}$$

and $1/\alpha$ is approximately equal to Φ in equation (2.59). Moreover, $(1 - {}_{1}s_{ii})$ in McGinnis's notation is approximately equal to $\omega\, \Delta t$, where ω is the parameter in equation (2.59). Thus the computer simulation experiments of the Cornell group were based on a discrete time version of Probability Law IV with parameter ξ equal to zero. This group has not yet published data to test its version of this law.

In their respective versions of Probability Law IV both Mayer and

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[5] $\lim_{|x| \to \infty} (1 - 1/x)^{-x} = e$

McGinnis assumed that the parameter ξ in equation (2.59) is zero, that the parameter Φ is the same for all states j, and that only the parameter ω and the conditional transition probability q_{jk} vary with state j. The fundamental difference between their versions of this probability law is the reference scale for time t. Mayer treated time t as age, or more exactly, as years in the labor force: time t is zero only at the moment that a person enters the labor force, which Mayer apparently took as 18 years of age for the purpose of his calculations. On the other hand, McGinnis treated time t in Probability Law IV as duration in a state j: time t is zero at the first moment in each state that a person enters in his lifetime. Which conceptualization of time t is better is at least as fundamental as the question of the form of $h_j(t)$, the instantaneous rate of leaving state j, but as I mentioned at the beginning of this chapter, I am deferring discussion of this question until Chapter 3.

2.8 Probability Law V

The mathematical equations defining Probability Law V are:

$$(2.70) \qquad h_j(t) = \frac{\beta \lambda_1 \exp[-\lambda_1 t] + (1-\beta) \lambda_2 \exp[-\lambda_2 t]}{\beta \exp[-\lambda_1 t] + (1-\beta) \exp[-\lambda_2 t]}$$

$$(2.71) \qquad \overline{G}_j(t) = \beta \exp[-\lambda_1 t] + (1-\beta) \exp[-\lambda_2 t]$$

$$(2.72) \qquad \overline{f}_j(t) = \beta \lambda_1 \exp[-\lambda_1 t] + (1-\beta) \lambda_2 \exp[-\lambda_2 t]$$

where $\beta \neq 0$, $\lambda_1 > 0$, $\lambda_2 \geq 0$, and time $t \geq 0$.

Probability Law V can be derived from models constructed through Approaches A, B, or C. In order to derive this probability law by using Approach A, we postulate that for a homogeneous population in state j the instantaneous rate of leaving state j, $h_j(t)$, declines with

time t as given by equation (2.70). Because of the complexity of this equation, it is not surprising that previous investigators have not employed this route to Probability Law V.

Originally Probability Law V was derived from a model assuming heterogeneity of the population in state j (Approach B). The necessary postulates for such a model are as follows. For proportion β of the population in state j the instantaneous rate of leaving is λ_1:

$$(2.73) \qquad c_j(y,0) = \beta$$

$$(2.74) \qquad h_j(y_1,t) = \lambda_1.$$

For the remaining proportion $(1 - \beta)$ the instantaneous rate of leaving state j is λ_2:

$$(2.75) \qquad c_j(y_2,0) = 1 - \beta$$

$$(2.76) \qquad h_j(y_2,t) = \lambda_2.$$

Substituting these expressions into equation (2.29) gives equation (2.71) as the expression for $\overline{G}_j(t)$, the expected proportion remaining in state j at time t.

In the best known version of Probability Law V the parameter λ_2 is assumed to be zero. As time t approaches infinity, $\overline{G}_j(t)$, the expected proportion remaining in state j, approaches $(1 - \beta)$; these are called "stayers." The other proportion β of the original population are called "movers" as all of them eventually leave state j. This version of Probability Law V, with the added assumption that $q_{jk}(t)$, the conditional probability of moving from state j to state k, is independent of time, has been named the Mover-Stayer Model.

After Blumen, Kogan, and McCarthy (1955) found that Probability Law I provided an unsatisfactory explanation of their data on

inter-industry mobility, they proposed the discrete time version of the Mover-Stayer Model to explain movement in the system. Let B be a square matrix with diagonal elements β_j, the proportion of "movers" in state j at time 0, and with zeros for all elements off the diagonal. Let R be a time-independent matrix of instantaneous transition rates with elements

$$r_{jj} = -\lambda_j \tag{2.77}$$

and

$$r_{jk} = \lambda_j q_{jk} \tag{2.78}$$

where λ_j is the movers' instantaneous rate of leaving state j and q_{jk} is the conditional probability of a move from state j to state k. Then the solution of the Mover-Stayer Model is

$$P(0,t) = I - B + B \exp[Rt] \tag{2.79}$$

where time t is calendar time.

Blumen, Kogan, and McCarthy used the inter-industry transition matrix for eight quarters to estimate parameters and then used these estimates to calculate expected transition matrices for four, eight, and twelve quarters. The agreement between the actual and predicted matrices was quite good for eight quarters; however, for four quarters too few men were predicted to be in the same industry as at time 0, and for twelve quarters too many men were predicted to be in the same industry as at time 0. As the authors pointed out, the discrepancies for twelve quarters might result from the unrealistic assumption that some people never move.

In another version of this model, both parameters λ_1 and λ_2 are

assumed to be greater than zero with $\lambda_1 > \lambda_2$: everyone is a mover, but one group leaves at a more rapid rate than the other group. As time t approaches infinity, $\bar{G}_j(t)$, the expected proportion remaining in state j at time t, approaches zero.

Bartholomew (1959) originally proposed this version of Probability Law V without giving it any interpretation but later (1967: 127) referred to it as if it were derived by assuming population heterogeneity (Approach B). Using data gathered by Silcock (1954) and by Lane and Andrew (1955) on the length of employment of workers in three firms, Bartholomew estimated the parameters of the probability law by equating the observed proportion remaining in state j at three, six, and eighteen months with the value of $\bar{G}_j(t)$ at these times. Then he used his estimates of the parameters to calculate the predicted distribution of the length of employment of workers, $n_j(0)\ \bar{f}_j(t)\ \Delta t$, and on the basis of inspection concluded that the predictions were adequate. In 1967 Bartholomew noted that Probability Laws II and V predicted these data about equally well.

Probability Law V can also be derived from Approach C. Any model postulating two distinct stages within state j and Markovian movement between these stages and out of state j leads to the equations specifying Probability Law V. Mayer (1968) constructed a model of this type in order to explain the dependency on age of occupational prestige mobility. In his model (cf. Figure 2.3), when an individual leaves the initial stage U, he either enters an absorbing stage PC within state j or leaves state j, i.e., enters L.

Like the Mover-Stayer Model of Blumen, Kogan, and McCarthy (1955), Mayer's model implies that parameter λ_2 of Probability Law V equals

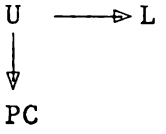

Figure 2.3 Structure of Mayer's (1968) model

zero. However the interpretation of the probability law differs in two significant ways. First Mayer interpreted time t as age, or more exactly as years in the labor force, while Blumen et al. interpreted time t as calendar time. More importantly, in using Approach C Mayer constructed his model so that the mover-stayer dichotomy is a property of the relationship between an individual and a social position; thus each person entering a new position has a chance of becoming a stayer. In using Approach B Blumen et al. postulated that the mover-stayer dichotomy is a property of persons. According to this conjecture Probability Law V describes the process of individuals leaving the state occupied at time 0, but since anyone leaving this state is a mover, Probability Law I describes the process of leaving any state entered after time 0.

Mayer tested his version of Probability Law V using the same data as in his test of Probability Law IV. Once again he used a synthetic cohort and solved equation (1.25) for P(0,t), requiring him to assume that $q_{jk}(t)$, the conditional probability of moving from state j to state k, is independent of time for all states j and k. Mayer's discussion of his estimation procedures indicates that he never obtained an analytic solution for P(0,t) but only an approximation to it. Although Mayer encountered difficulties in estimating parameters, he did calculate approximate values for the expected mobility to various prestige categories at given ages, and he compared these with the

observed values. Using the index of dissimilarity as a measure, Mayer found that his version of Probability Law V did not predict his data as well as Probability Law IV.

Mayer justifiably retained his interest in his version of Probability Law V because it represents an alternative to assuming nonstationarity or population heterogeneity. However the considerable difficulties involved in solving equation (1.25) for P(0,t) with this structurally simple model argue forcibly for studying the process of individuals leaving one particular state j before trying to explain the entire process of movement among states in a system.

2.9 Probability Law VI

The mathematical equations defining Probability Law VI are:

$$(2.80) \qquad h_j(t) = \frac{\sum_{z=1}^{4} \beta_z \lambda_z \exp[-\lambda_z t]}{\sum_{z=1}^{4} \beta_z \exp[-\lambda_z t]}$$

$$(2.81) \qquad \overline{G}_j(t) = \sum_{z=1}^{4} \beta_z \exp[-\lambda_z t]$$

$$(2.82) \qquad \overline{f}_j(t) = \sum_{z=1}^{4} \beta_z \lambda_z \exp[-\lambda_z t]$$

where $\beta_z \neq 0$, $\beta_1 + \beta_2 + \beta_3 + \beta_4 = 1$, $\lambda_z \geq 0$, and time $t \geq 0$.

Like Probability Law V, whose mathematical form it closely resembles, Probability Law VI can be derived from models constructed through Approach A, B, or C. In using Approach A, one postulates that for a homogeneous population in state j the instantaneous rate of leaving state j, $h_j(t)$, declines with time t according to equation (2.80). In

using Approach B, one postulates that the population in state j consists of four groups in proportions β_1, β_2, β_3, and β_4 for which the instantaneous rate of leaving state j is λ_1, λ_2, λ_3, and λ_4, respectively. In using Approach C, one postulates that state j consists of four distinct stages and that movement among these stages and out of state j is Markovian.

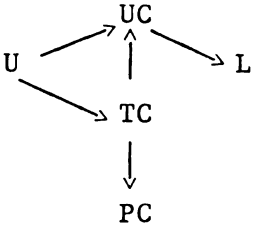

Figure 2.4 Structure of Herbst's (1963) model

Herbst (1963), the sole proponent of Probability Law VI, utilized Approach C. In his model (cf. Figure 2.4), he postulated that (1) upon entering state j all individuals are in an undecided stage U, (2) those leaving U go either to a temporarily committed stage TC or to an uncommitted stage UC, (3) temporarily committed persons may enter either a permanently committed (absorbing) stage PC or the uncommitted stage UC, and (4) everyone in the uncommitted stage UC eventually leaves state j, i.e., goes to L. Probability Law VI with time t referring to duration in state j and with parameter λ_4 equal to zero results from these assumptions.

Using data collected by Hedberg (1961) on the distribution of the length of employment of workers in two Swedish steel factories, Herbst estimated the parameters of Probability Law VI through an undescribed procedure. On the basis of inspection he obtained an excellent fit between the observed proportion remaining in the two firms after

various durations and the proportion predicted using the parameter estimates. However Herbst's version of Probability Law VI has six independent parameters to be estimated giving it an advantage (of indeterminate magnitude) over those probability laws previously discussed, which have at most three independent parameters.

Herbst used his parameter estimates to calculate the instantaneous rates of transition among the stages of the model. While these values seem reasonable, Herbst's data are not sufficient to rule out other models with four stages within state j or models constructed through Approach A or B.

2.10 Probability Law VII

The mathematical equations defining Probability Law VII are:

$$(2.83) \qquad h_j(t) = \frac{\sum_{z=1}^{3} \beta_z \lambda_z \exp[-\lambda_z t]}{\sum_{z=1}^{3} \beta_z \exp[-\lambda_z t]}$$

$$(2.84) \qquad \bar{G}_j(t) = \sum_{z=1}^{3} \beta_z \exp[-\lambda_z t]$$

$$(2.85) \qquad \bar{f}_j(t) = \sum_{z=1}^{3} \beta_z \lambda_z \exp[-\lambda_z t]$$

where $\beta_z \neq 0$, $\beta_1 + \beta_2 + \beta_3 = 1$, $\lambda_z \geq 0$, and time $t \geq 0$.

Like Probability Laws V and VI, Probability Law VII can also be derived from models constructed through Approach A, B, or C. In using Approach A, one postulates that for a homogeneous population in state j the instantaneous rate of leaving state j, $h_j(t)$, decreases as time t increases as given by equation (2.83). In using Approach B, one postulates that the population in state j consists of three groups in

proportions β_1, β_2, and β_3 for which the instantaneous rate of leaving state j is λ_1, λ_2, and λ_3, respectively. In using Approach C, one postulates that state j consists of three distinct stages and that movement among these stages and out of state j is Markovian.

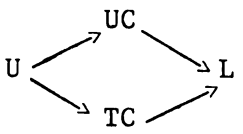

Figure 2.5 Structure of Conner's (1969) model

Employing Approach C, Conner (1969) made assumptions similar to those of Herbst (1963) except that he reasoned that no one could ever stay permanently in a state j, which eliminated Herbst's stage PC. In addition he argued that temporarily committed persons left state j directly without passing through the uncommitted stage UC. The structure of Conner's model is diagrammed in Figure 2.5 with the labels of the stages to be interpreted as in Herbst's model. Probability Law VII with time t referring to duration results from these assumptions.

Conner tested Probability Law VII with data on the number of continuous years of employment as a farm laborer from age sixteen for 144 Mexican-American males born in 1920 or later. He estimated the parameters by trying different values for the instantaneous rates of transition among the stages of the model and adjusting them to improve the accuracy of their prediction. On the basis of inspection he obtained close agreement between the actual and predicted distributions of the duration of continuous employment as a farm laborer.

CHAPTER 3

The Process of Individuals Leaving a Social Position: Basic Issues

In the present chapter I discuss the following issues pertaining to the process of individuals leaving a social position: (1) the correspondence between the theoretical construct state j and observable phenomena; (2) the identification of equivalent social positions; (3) the identification of equivalent individuals, i.e., homogeneous subpopulations; (4) the correspondence between the theoretical construct time t and observable measures of time; (5) the validity of the Markov assumption; (6) the validity of Approaches A, B, and C, and (7) the validity of Probability Laws I through VII.

3.1 The correspondence between the theoretical construct state j and observable phenomena

In previous empirical investigations pertaining to stochastic models of individuals leaving a social position, a state j has variously been conceptualized as an occupation, industry, occupational prestige category, firm, factory, or geographical area. As I indicated in the Introduction, the explanandum of this research is job mobility, and therefore a job is conceptualized as a state j in this study.[1] Is there a reason, other than personal preference, for selecting one particular

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[1] In Chapter 5 I specify in detail the working definition of a state j that I have used in the empirical investigation. For the present discussion it suffices to consider a continuous period (excluding vacations, lay-offs, illnesses, and other temporary interruptions)

conceptualization rather than another? The mathematical theory developed for Approach C in Section 2.4 can be used to support an affirmative answer.

Suppose that a particular occupation j is identified as state j. Now an individual may have from one to d consecutive jobs in occupation j where d is some possibly large but definitely finite number. Let J_z represent the z^{th} job in a sequence of jobs in occupation j, and let L depict the condition of having left occupation j. Then the following diagram illustrates the simplest possible substructure of the process of leaving occupation j.

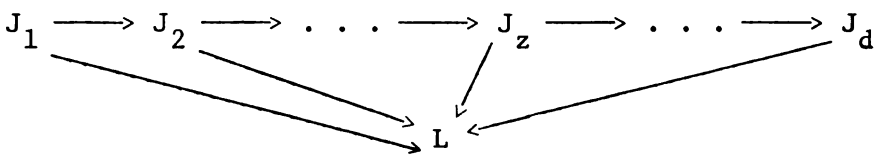

Figure 3.1 Structure of the process of leaving an occupation

Let us assume that the instantaneous rate of leaving the z^{th} job in occupation j, $h_j(z,t)$, is μ_z, a time-independent constant specific for the z^{th} job in occupation j, and that the conditional probabilities of transitions from the z^{th} job in occupation j to the $(z + 1)^{th}$ job in occupation j and to L are also time-independent constants specific for the z^{th} job in occupation j. Since these assumptions parallel those made for Approach C (the z^{th} job corresponds to stage z), the equation for $\overline{G}_j(t)$, the expected proportion remaining in occupation j at time t, is exactly equation (2.38):

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spent in one occupation with one employer in one geographical location as a state j. To obtain a closed system, other fulltime activities that may take the place of work (being retired, unemployed, or in school) are also treated as states in the state space.

$$(3.1) \qquad \bar{G}_j(t) = \sum_{z=1}^{d} \beta_z \exp[\lambda_z t]$$

where λ_z equals $-\mu_z$ for $z = 1, 2, \ldots, d$.

Under the special case of μ_z equal to κ for $z = 1, 2, \ldots, d$, this equation reduces to

$$(3.2) \qquad \bar{G}_j(t) = \exp[-\kappa t]$$

which is equation (2.11) of Probability Law I. However, as I reported in Chapter 2, evidence in a wide variety of situations has not supported Probability Law I. This suggests that we should tentatively assume that μ_z does not equal κ for $z = 1, 2, \ldots, d$. Consequently if an occupation j is conceptualized as a state j, the simplest expression that we might reasonably expect for $\bar{G}_j(t)$ is a sum of d exponential terms as in equation (3.1). If the instantaneous rates of transition among jobs in occupation j are <u>not</u> independent of time, then the expression for $\bar{G}_j(t)$ is even more complex than equation (3.1).

If an industry, occupational prestige category, firm, factory, or geographical area is conceptualized as a state j, my reasoning parallels that above.[2] However, in addition to decomposing a state j into a sequence of d consecutive jobs, I would also differentiate among $w = 1, 2, \ldots, c$ types of jobs.[3] Then the z^{th} job in state j might be J_{z1}, J_{z2}, . . ., or J_{zc}, and the diagram of the substructure of the process of leaving state j would be correspondingly more complex.

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[2]This type of analysis only applies to mobility among geographical areas sufficiently large to exclude changes of residence that do not necessitate job changes.

[3]It might be necessary to differentiate among types of jobs when an occupation j is conceptualized as a state j, but I ignored this complication in my discussion above so that the initial presentation of the basic idea would be more clearly understood.

Let us assume that the instantaneous rate of leaving the z^{th} job of type w in state j, $h_j(z,w,t)$ is μ_{zw}, a time-independent constant specific for z and w, and that conditional transition probabilities among jobs within state j and to L are also time-independent constants. Then the equation for $\bar{G}_j(t)$, the expected proportion remaining in state j at time t, is still a sum of exponential terms:

$$(3.3) \qquad \bar{G}_j(t) = \sum_{z=1}^{d} \sum_{w=1}^{c} \beta_{zw} \exp[\lambda_{zw} t]$$

where λ_{zw} equals $-\mu_{zw}$ for w = 1, 2, . . ., c, and z = 1, 2, . . ., d. The expression for $\bar{G}_j(t)$ is even more complex than this if the instantaneous rates of transition among the jobs composing state j are not time-independent constants.

In order for the equation for $\bar{G}_j(t)$ to be as simple in form and to contain as few independent parameters as possible, I conclude that it is desirable to conceptualize a state j as the simplest observable position, which in the present research is a job. Since, as I have indicated, the process of leaving an occupation, industry, occupational prestige category, firm, factory, or geographical area can be decomposed into the process of moving among a sequence of jobs of possibly different types, information on job mobility can help us to understand these other forms of social mobility. In addition, as I show in the next section, conceptualizing a job as a state j can assist in evaluating systems of classifying social positions and can provide a foundation for a substantive explanation of the leaving process.

3.2 The identification of equivalent social positions

While the importance of this issue has previously been recognized (cf. the discussion of "lumpability" by Kemeny and Snell, 1960, and by

McFarland, 1970), it has not yet stimulated extensive empirical research. In fact McFarland (1970: 464) has stated:

> Occupations could be classified into states for a stochastic process in a large variety of ways, and searching for one which would make the process a Markov chain (even if such a classification existed) is somewhat like looking for the proverbial needle in a haystack.

Although a classification of jobs which makes job mobility a Markov process probably cannot be devised,[4] I do think that some ways of classifying jobs provide a more satisfactory basis for a theory of social mobility than others and that the adequacy of various classification systems can and should be empirically investigated. Such an investigation aims to identify equivalent social positions and is no more like looking for a needle in a haystack than any other scientific research. A research design for such an investigation is given in Section 5.3a.

In the present study I examine the effect on the process of individuals leaving jobs of three job attributes for which I have adequate information -- occupational classification, industrial classification, and geographical location. While I do not regard these as completely sufficient attributes for establishing which jobs are equivalent social positions with regard to the leaving process, I do have reasons, discussed below, for considering them important. The substantive, analytic framework outlined below also underlies the discussion in Sections 3.3 through 3.6.

Let three types of job terminations be distinguished: those occuring unintentionally, those initiated by the employer,[5] and those initiated by the jobholder. These are listed in the reverse of the usual

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[4] I doubt that a classification of jobs which makes job mobility a Markov process can ever be devised because I expect the probability of leaving a job to depend on duration in the job (cf. Section 3.4) and

order of frequency of occurrence and sociological interest. I treat the last two as instances of intentional job terminations.

Death and disability are the primary reasons that jobs are unintentionally terminated. These events are associated with the physical hazards and stresses of a job, and consequently with the occupation and occasionally with the industry of the job. As health care varies throughout the United States, the rate of unintentional job terminations may also vary somewhat with geographical location. While a complete explanation of the process of leaving jobs would take account of these effects, their net impact on the instantaneous rate of individuals leaving jobs is ordinarily slight due to the relatively small proportion of unintentional job terminations.

In practice the magnitude of the instantaneous rate of individuals leaving a job j, $h_j(t)$, primarily depends on the level of intentional job terminations. The analytic framework that I employ in explaining intentional job terminations rests on the assumption that the probability of an individual (jobholder or employer) initiating a change in his situation increases if the individual judges that his present situation is unsatisfactory and that he can probably obtain another more satisfactory situation. Therefore, I expect the magnitude of $h_j(t)$ to increase with the employer's and jobholder's dissatisfaction with the present situation and with their perceived ability to find a more satisfactory alternative situation.

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the conditional probability of moving from one job to another to depend on previous work experiences (cf. Section 4.6).

[5]The proportion of individuals in the present study who reported any periods of self-employment is so small that I am ignoring this possibility and its distinctive problems.

I assume that an employer is highly likely to terminate jobs of employees (by firing, transferring, promoting, or retiring them) if he no longer foresees a need for their work activities, or if he expects that the continuation of the present assignment of employees to jobs will lead to unsatisfactory work performance and that he can obtain another more satisfactory assignment of personnel. The employer's ability to find other satisfactory employees for the jobs in question depends primarily on the supply of qualified job applicants, and therefore on the geographical location and occupational classification of the jobs.

I assume that a jobholder is very likely to terminate his job if he is dissatisfied with it and thinks that he can probably obtain a more satisfactory job (cf. March and Simon, 1958). The social rewards obtained in a job, and presumably the individual's satisfaction in his job, are highly correlated with occupation, and to a lesser extent with industry and location. The ability to find other employment depends jointly on the structure of job vacancies (i.e., the number of vacancies in different types of jobs) and on the structure of job-seekers (i.e., the number of individuals with different qualifications who are looking for a job), both of which vary widely with geographical location. I expect the individual's perception of his ability to find other employment to reflect his actual opportunities with considerable accuracy. At the same time the individual's perception of his ability to find more satisfactory employment is inherently relative to his present position and his evaluation of it, and therefore depends on the occupational classification of his present job.

Since unintentional job terminations are comparatively few in number, I expect that the net effect of occupation, industry, and

location to be as follows: the greater the social rewards of a job in a particular occupation, industry, or location, the smaller the magnitude of $h_j(t)$; the greater the opportunities for employment in a particular location, the larger the magnitude of $h_j(t)$.

3.3 The identification of equivalent individuals

I examine the effect on the process of individuals leaving jobs of three attributes of an individual that are fixed throughout his work history: educational level,[6] the primary location in which he was reared, and migrant farm background. Of these I expect educational level to have the greatest influence on the instantaneous rate at which individuals leave jobs.

It is well known that the individual's educational level correlates highly with the social rewards obtained in his job. Consequently the level of rewards that the individual realistically expects to obtain in his job should rise with his educational level. I therefore expect that in any given job j, the higher the individual's educational level, the more likely he is dissatisfied with his job. Reynolds' (1951) finding that manual workers with a high school education were more likely to want to leave their present job than those without a high school education supports this conjecture. In addition, because employers tend to hire individuals preferentially on the basis of education and because job-seekers are sensitive to the demand for individuals with particular qualifications, I expect the individual's perception of his ability to find more satisfactory employment to rise with his educational level.

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[6] An individual does not always complete his education prior to his first fulltime job, but I have ignored this complication.

In sum I expect the instantaneous rate of leaving job j, $h_j(t)$, to increase with educational level.

I expect being reared in a less industrialized location and having a migrant farm background to affect $h_j(t)$ slightly in the same direction as having a lower educational level. I reason that being reared in a location with an economy more oriented towards agriculture and less oriented to industry and having a migrant farm background are likely to lower the individual's expectations of the level of rewards which he can obtain from jobs and to magnify his assessment of any improvements in his social position, e.g., obtaining a job in the industrial sector. Therefore I expect the level of dissatisfaction with the present job, and hence the magnitude of $h_j(t)$ to be depressed for individuals reared in less industrialized locations and for individuals having a migrant farm background. However, the effect of these attributes should be much less than that of educational level.

3.4 The correspondence between the theoretical construct time t and observable measures of time

Should time t of a probability law describing the process of leaving a social position be conceptualized as calendar time (cf. Blumen, Kogan, and McCarthy, 1955), the individual's age or years in the labor force (cf. Mayer, 1968), or the individual's duration in the social position (cf. Silcock, 1954; Lane and Andrew, 1955; Bartholomew, 1959; Hedberg, 1961; Herbst, 1963; McGinnis, 1968; Conner, 1969)?

There are reasons for thinking that all three measures of time have relevance for the process of leaving jobs. Calendar time is important because the structure of job vacancies and of job-seekers, and concomitantly an individual's ability to find other employment, fluctuates with this measure of time. However, jobholders are more

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likely to terminate jobs intentionally when desirable jobs are plentiful, and employers are more likely to fire workers when such jobs are scarce. The extent to which these two factors maintain a balance in the number of intentional job terminations is unknown.

Age at entering the job should also affect the process of leaving jobs. The number of job terminations due to death, disability, and retirement increases with age. At the same time the individual's ability to find another job, and concurrently the number of worker-initiated job terminations, probably declines with increases in age. The extent to which increases in unintentional terminations with increasing age are balanced by declines in terminations initiated by the job-holder is also unknown.

Duration in a job should have an important influence on the leaving process because a worker who endures in a job tends to acquire more monetary rewards, seniority rights, and other perquisites which probably improve his evaluation of his present job in comparison with perceived alternatives. Furthermore perceived ability to find other acceptable employment probably declines with increasing duration in the job as the worker's skills become more tied to his present job and as up-to-date knowledge of the job market diminishes. Since most employers try to discover and eliminate unsatisfactory personnel as soon as possible after employment begins, I also expect the number of employer-initiated job terminations to decline with increases in duration. The net effect should be that the instantaneous rate of leaving a job declines as duration increases.

3.5 The validity of the Markov assumption

The crux of the matter is whether or not the process by which otherwise equivalent individuals leave equivalent jobs is affected by

events occurring after individuals enter the labor force. Does the instantaneous rate of leaving job j, $h_j(t)$, vary with the previous experiences of otherwise equivalent individuals? Of particular interest is the possible influence of previous work experience, e.g., previous experiences in a particular occupation or industry. If previous work experiences of individuals affect the process of leaving jobs, then an adequate first order Markov model of job mobility can not be constructed.[7]

It seems reasonable to think that previous work experiences do have some influence on both the individual's satisfaction with his present job and his perceived ability to find satisfactory alternative employment. People compare their present situation not only with ideal standards but also with concrete experiences in the past. And in trying to assess prospects for a favorable job change, people are probably influenced by previously successful and unsuccessful job changes.

Three questions must be answered: (1) Do previous experiences with a particular occupation, industry, or location have any consistent effect on otherwise equivalent individuals in job j? (2) What is the magnitude of the effect of these previous experiences if their effect is consistent? (3) If previous experiences do have a consistent and nonnegligible effect on $h_j(t)$, over what time span does the effect hold? In particular do experiences in job i immediately prior to job j have the same effect as the same type of experiences still earlier in the individual's history?

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[7] Even if previous experiences do not affect the process of leaving job j, a first order Markov model of job mobility is still inadequate if $q_{jk}(t)$, the conditional probability of a transition from job j to job k, depends on previous experiences.

In the present study the first and second questions are specified as follows: is the instantaneous rate of leaving job j, $h_j(t)$, consistently and significantly different for otherwise equivalent individuals who vary with regard to previous experience in the occupation or industry of the present job j? I anticipate a negative answer to this question. While those with previous experience in the same occupation or industry as job j may be consistently more likely to be satisfied with job j, I do not expect differences in satisfaction to be large, nor do I expect variations in these previous experiences to affect significantly the perceived ability to find satisfactory alternative employment. Therefore I expect the magnitude of $h_j(t)$ to be relatively independent of previous work experiences in the same occupation or industry as job j, whether these previous experiences were in the job i immediately prior to job j or still earlier in the individual's career.

3.6 The validity of Approaches A, B, and C

As I mentioned at the beginning of Chapter 2, a stochastic model of individuals leaving a social position consists of not only a probability law describing the leaving process but also the set of assumptions used to derive the probability law. Since many probability laws can be derived by more than one set of assumptions, evaluating a model involves distinguishing among these different sets of assumptions as well as evaluating the probability law derived from them. The present section is devoted to the problem of evaluating and distinguishing among the approaches, or sets of general assumptions, used to derive probability laws. While my discussion is limited to the three approaches presented in Chapter 2, I do not imply that other and better approaches can not be devised.

I presume that the problem of evaluating these approaches is raised after resolution of the first five issues discussed in this chapter and is not a hidden attempt to deal with the subject of one of these other issues. Thus I assume that each approach attempts to explain the process by which equivalent social positions are left by individuals who are equivalent at the moment of entering the position.

The distinctive feature of Approach A is the assumption of non-stationarity, i.e., the assumption that the instantaneous rate of leaving position j, $h_j(t)$, is the same specified function of time for equivalent individuals in position j. To date no one has furnished reasons why $h_j(t)$ should be any particular function of time. As long as there is no substantive argument underlying models constructed through Approach A, one cannot empirically evaluate the approach, even though one can test probability laws derived by means of it.

The basic assumptions of Approach B are that individuals in social position j are heterogeneous on variable y with their position on y fixed during their stay in that position, and that the instantaneous rate of leaving position j is a function of both y and time t. So far everyone has made the natural assumption that for each individual the instantaneous rate of leaving position j does not depend on time t, but only on y, although the equations presented in Chapter 2 for deriving probability laws by this approach are not limited to this assumption. A fundamental weakness in the utilization of Approach B thus far has been the lack of substantive reasons for selecting one probability distribution on y rather than another.

The distinctive problem to consider with regard to Approach B is the nature of the variable y. Previous investigators have not implied

that variable y is to be associated with such standard sociological variables as sex, ethnicity, educational level, and so forth. Thus even members of a socially homogeneous population are implicitly assumed to vary on y and therefore on the value of the instantaneous rate of leaving position j.

One needs to know if y is assumed to be a fixed characteristic of the individual. That is, does the instantaneous rate at which an individual leaves each social position occupied during his lifetime depend on this same variable y? If the answer is yes, then it seems reasonable to conjecture that the population only appears to be socially homogeneous but actually varies on one or more dimensions not yet examined. In this case empirical support for Approach B should stimulate further research on the identification of equivalent individuals as discussed in Section 3.3.

If y is a fixed characteristic of the individual and if, in addition, y has a similar effect in every type of social position, then on the average individuals with values of y causing a high proneness to leave will leave positions sooner and thus occupy more positions in a given period of time than individuals with values of y causing a low proneness to leave. An admittedly crude test of Approach B under these conditions is to compare the rates of leaving position j for individuals with few previous positions and for individuals with many previous positions. If the differences between the two groups exceed random variation, then variable y, i.e., population heterogeneity, probably exists. This conclusion follows for any probability law although the test is more sensitive for some probability laws than for others.

For instance it is especially easy to distinguish between the version of Probability Law V with parameter λ_2 equal to zero as constructed by Blumen, Kogan, and McCarthy (1955) through Approach B (the Mover-Stayer Model) and the same version of Probability Law V as constructed by Mayer (1968) through Approach C. According to the former, Probability Law I should describe the leaving process for people who have moved at least once. According to the latter, no matter how many or how few previous positions individuals have had, Probability Law V should still describe the leaving process.

If y is not a fixed characteristic of the individual, or if it is a fixed characteristic but does not have a similar effect in every social position that the individual occupies, then Approach B is considerably more difficult to test, the exact nature of the test being dependent upon one's assumptions concerning y.

As I indicated in Section 2.4, Approach B closely resembles Approach C, subtype (b), which postulates parallel stages in a social position j. In fact the mathematical equations used to derive a probability law are exactly the same for these two approaches. The sole significant difference is that in the former the variable y refers to properties of individuals while in the latter the variable y refers to properties of social positions.

In the case of Approach C, subtype (b), if y is a fixed characteristic of a social position and has a similar effect on the rate at which every occupant leaves, then on the average positions with values of y causing a high proneness to leave will have more occupants in a given period of time than positions with values of y causing a low proneness to leave. Thus the same type of crude test described for Approach B

can be used to identify this form of heterogeneity of social positions. In this instance one compares the rate of leaving for positions with few previous occupants in a given time span with positions with many previous occupants in this same period. If the differences between the two groups exceed random variation, then heterogeneity of the positions probably exists. As this test requires information on the history of particular positions, it cannot be utilized with the data available in the present study.

To date Approach C has been used to construct models of social positions containing stages both in series and in parallel (subtype (c)). Initial homogeneity has been assumed although this is not intrinsic to the approach. After leaving the initial stage individuals are postulated to enter other stages distinguishable from one another in terms of the expected time before leaving position j. Two of the three models which have been proposed have made substantive, testable (although untested) assertions that can be used to distinguish among different interpretations of the resulting probability law. Unfortunately testing the distinctive aspects of these models requires information on activity within a position j, and this is not contained in the histories forming the data in this research.

At present an analysis of the validity of Approaches A, B, and C must be less than satisfactory. Substantive arguments are lacking in support of either Approach A (the assumption of nonstationarity) or Approach B (the assumption of population heterogeneity), although one form of Approach B can still be tested with continuous time work histories. On the other hand, while substantive assertions undergird two models constructed through Approach C, subtype (c), testing these

assertions requires data on activity within a social position, and these data are not yet available. This area greatly needs both theoretical development and empirical investigation.

3.7 The validity of Probability Laws I through VII

The present investigation is restricted to evaluating the ability of those previously proposed probability laws discussed in Chapter 2 to describe the process of equivalent individuals leaving equivalent jobs. Thus I presume that the first five issued discussed in this chapter have been resolved when attention turns to the present problem.

Although Probability Law I has previously been found unsatisfactory in every empirical study concerned with social mobility, it deserves reexamination because of its fundamental importance as the "natural" probability law. However, since I expect the instantaneous rate of leaving a job to vary with duration (cf. Section 3.5), I do not expect to find Probability Law I satisfactory in the present study.

The other six probability laws reviewed in Chapter 2 have been reasonably successful in predicting observed social mobility, however defined. Neither theoretical arguments nor prior empirical findings are sufficiently weighty to favor any one of these probability laws over the others in advance. Thus this study undertakes the evaluation of the relative as well as the absolute ability of these probability laws to predict the observed movement of Mexican-American men out of jobs.

The least satisfying aspect of investigating these probability laws results from the fact that, except for Probability Law I, each can be derived from more than one of the three approaches presented in Chapter 2 and that these sets of assumptions cannot be distinguished

in this study (cf. Section 3.6). Thus, even if one of these six probability laws is clearly superior to the others in its ability to predict observed movement of Mexican-American men out of jobs, its theoretical interpretation must presently be ambiguous.

CHAPTER 4

The Process of Individuals Entering a New Social Position: Basic Issues

The present chapter is concerned with the process of individuals entering a new social position, given that they are leaving some other social position. Specifically my efforts are directed toward developing an explanation of the conditional probability of an individual moving from state j to state k at time t:

$$(4.1) \qquad q_{jk}(t) = \text{prob}[\text{entering state k at time t} \mid \text{leaving state j at time t}].$$

Surprisingly little has been said about this topic by those interested in stochastic models of individuals moving among social positions.[1] For instance, the researchers whose work is reviewed in Chapter 2 have either concerned themselves solely with the process of individuals leaving a social position and ignored the destination of the leavers (cf. Silcock, 1954; Lane and Andrew, 1955; Bartholomew, 1959; Hedberg, 1961; Herbst, 1963; Conner, 1969), or else have implicitly assumed that $q_{jk}(t)$ is a time-independent constant q_{jk} with no explanation or justification thereof attempted (cf. Blumen, Kogan, and

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[1] In developing vacancy chain models, Harrison C. White (1968, 1969, 1970) has utilized the concept of the conditional probability of a vacant social position moving from state k to state j. Although this concept and $q_{jk}(t)$ differ mathematically, both refer to the event of an individual moving from state j to state k at time t.

McCarthy, 1955; Mayer, 1968; McGinnis, 1968). Notable exceptions to these two practices are mentioned at appropriate points in the discussion below.

In this chapter I discuss the following topics pertaining to the process of individuals entering a new social position, given that they are leaving some other social position: (1) the correspondence between the theoretical construct state j and observable phenomena; (2) models of the conditional transition probability $q_{jk}(t)$; (3) the identification of equivalent social positions; (4) the identification of equivalent individuals, i.e., homogeneous subpopulations; (5) the correspondence between the theoretical construct time t and observable measures of time; and (6) the validity of the Markov assumption.

4.1 The correspondence between the theoretical construct state j and observable phenomena

To maintain continuity in this research, I naturally make the same correspondence as in the previous chapter. In that chapter I argued that making a correspondence between a job and the theoretical construct state j not only had heuristic value but also formed a sound basis for a substantive understanding of the process of individuals leaving a social position. Arguments paralleling those in the previous chapter could be made with regard to developing an explanation of the process of individuals entering a new social position, but I am omitting these to avoid repetitiveness.

My primary reason for discussing this topic in the present chapter is to mention one technical problem that may arise when a job is identified as a state j and to indicate a possible solution to this problem. Suppose, for example, that jobs with the same occupational classification,

industrial classification, and geographical location are treated as equivalent social positions. It then becomes logically possible for a man who leaves a job of type j to enter a new job also of type j. This implies that $q_{jj}(t)$, the conditional probability of a transition from state j to state j, is not zero, which violates the assumption made in equation (1.15). This does not create any mathematical difficulties as long as one treats separately the process of leaving a state and the process of entering a new state, as I have done in this research. But if one is studying the overall mobility process, this violation of a basic assumption presents a serious problem.

One can, however, circumvent the violation of the assumption in equation (1.15) by adding a dummy dimension to the state space. The added dimension might indicate the number of the job, or possibly the oddness or evenness of the number of the job. It then becomes logically impossible to leave a job of type j and enter a new job of type j. Hence $q_{jj}(t)$ is always zero, as the basic assumption requires.

Normally one increases the size of the state space with considerable reluctance because such an increase generally reduces the amount of information pertaining to any particular state. But unless one finds that the number of the job actually affects the process of leaving a job or of entering a new job, the addition of a dummy dimension such as I have described does not decrease the information pertaining to any particular state.

4.2 Models of the conditional transition probability $q_{jk}(t)$

In the absence of any information about the different individuals and different positions in a system, a reasonable initial assumption is that all individuals and all positions are equivalent. In this case

each individual leaving a position at time t is equally likely to enter any other position in the system which is vacant at time t.[2] Random sampling of the vacant positions in the system is the model for this explanation of the process of an individual entering a new social position.[3]

Let the positions in the system be classified into k = 1, 2, . ., c different states and let $v_k(t)$ be the number of vacancies in state k at time t. Because the system is assumed to be closed (cf. Section 1.4a), each person who leaves a state must move to some state in the system. In other words, we assume:

$$\sum_{k=1}^{c} q_{jk}(t) = 1. \tag{4.2}$$

Obviously individuals leaving jobs do not always enter a new job within the same social system: some individuals die, some emigrate from the geographic boundaries of the social system, and still others continue to live within the geographic boundaries of the system but become unemployed, retire, and so forth. In order that equation (4.2) be satisfied, these alternatives must be included as one or more of the c states in the model of the system.[4] Because transitions in the system are assumed

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[2] An individual may only enter a position which is vacant at time t; otherwise two individuals could occupy the same position at time t, which contradicts my assumption at the beginning of Chapter 1.

[3] Since an individual may not enter the position which he is leaving, the actual model is random sampling of the vacant positions in the system, excluding the position which the individual is leaving. The exclusion of this one position should ordinarily make little difference; consequently this distinction is ignored for mathematical convenience.

[4] However, "vacancies" in the states of death, retirement, unemployment, and so forth cannot be counted, only inferred from the observed rate at which individuals move into these states.

to be independent (cf. Section 1.4b), we also assume that a move into or out of any state k by any particular individual does not significantly affect the number of vacancies in that state:

$$(4.3) \qquad v_k(t) \sim v_k(t) - 1.$$

Under these conditions the equation for the random sampling model is:

$$(4.4) \qquad q_{jk}(t) = v_k(t) \Big/ \sum_{k=1}^{c} v_k(t).$$

This model is unrealistic. First of all, it assumes that the state j which the individual leaves is irrelevant. Secondly, it assumes that attributes of individuals have no effect on conditional transition probabilities. Finally, it assumes that all vacant positions are equivalent and can therefore be categorized in <u>any</u> manner that an investigator wishes. In order to account for these objections, equation (4.4) can be modified to read:

$$(4.5) \qquad q_{jk}(t) = \alpha_{jk}(t)\, v_k(t) \Big/ \sum_{k=1}^{c} v_k(t),$$

where $\alpha_{jk}(t)$, the attraction of state k for individuals in state j, measures the deviation from the value of 1.0 predicted by random sampling of the vacancies in the system.

If state $k = (x_k, y_k)$, where x_k and y_k represent, respectively, the geographical location and occupation of positions in state k, then by definition equation (4.1) can also be written:[5]

$$(4.6) \qquad q_{jk}(t) = \text{prob}[\text{entering } (x_k, y_k) \mid \text{leaving } (x_j, y_j)].$$

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[5]The expression "at time t" is omitted from the right side of equations (4.6) through (4.10) below to improve their readability.

This equation can be written in two other, mathematically equivalent ways:

$$(4.7) \quad q_{jk}(t) = \text{prob}[\text{entering } y_k \mid \text{leaving } (x_j,y_j)] * \text{prob}[\text{entering } x_k \mid \text{entering } y_k; \text{ leaving } (x_j,y_j)]$$

and

$$(4.8) \quad q_{jk}(t) = \text{prob}[\text{entering } x_k \mid \text{leaving } (x_j,y_j)] * \text{prob}[\text{entering } y_k \mid \text{entering } x_k; \text{ leaving } (x_j,y_j)].$$

While these three equations for $q_{jk}(t)$ are mathematically equivalent, they suggest three different models of the process of entering a new job. The first describes a model in which individuals leaving a job in location x_j and occupation y_j sample the vacant positions in every location and occupation in the system simultaneously. The second points to a model in which individuals select a new occupation and then sample from vacancies in different locations for this particular occupation. The third implies a model in which individuals choose a new location and then sample from the vacancies in different occupations within this location.

If the geographic boundaries of the system are large, e.g., the United States, then the first model would rarely seem suitable. The second model appears reasonable for individuals leaving jobs in the professions, e.g., college professors. With regard to the Mexican-Americans in the present study, the findings of Choldin and Trout (1969) indicate that most men moved to a new location and then searched for a job in that location. This implies that the third model is appropriate for the present research.

If, analogous to equation (4.5), we postulate that

$$(4.9) \qquad q_{x_j y_j | x_k}(t) = \text{prob}[\text{entering } x_k \mid \text{leaving } (x_j, y_j)] = \alpha_{x_j y_j | x_k}(t)\, v_{x_k y.}(t) / v_{x.y.}(t)$$

and that

$$(4.10) \qquad q_{x_j y_j x_k | y_k}(t) = \text{prob}[\text{entering } y_k \mid \text{entering } x_k, \text{ leaving } (x_j, y_j)] = \alpha_{x_j y_j x_k | y_k}(t)\, v_{x_k y_k}(t) / v_{x_k y.}(t),$$

where . indicates summation over the missing index, then equation (4.8) reduces to equation (4.5) with

$$(4.11) \qquad \alpha_{jk}(t) = \alpha_{x_j y_j | x_k}(t)\, \alpha_{x_j y_j x_k | y_k}(t).$$

Equation (4.9) states that the conditional probability of moving to location x_k from location x_j and occupation y_j is proportional to the fraction of vacancies in the system which occur in location x_k; equation (4.10) states that the conditional probability of entering a job in occupation y_k, given that the individual moves to location x_k from location x_j and occupation y_j, is proportional to the fraction of vacancies in location x_k which occur in occupation y_k.

With an additional assumption we can convert equation (4.9) into a more familiar form. Let $n_{x_k y.}(t)$ represent the actual number of persons in the system in location x_k at time t and let $0_{x_k y.}(t)$ represent the crude or overall vacancy rate of location x_k at time t. By definition we can write:

$$(4.12) \qquad v_{x_k y.}(t) = 0_{x_k y.}(t)\, n_{x_k y.}(t),$$

where $v_{x_k y.}(t) \geq 0$ and $0_{x_k y.}(t) \geq 0$. Substituting equation (4.12) into equation (4.9), we obtain:

$$(4.13) \qquad q_{x_j y_j | x_k}(t) = \frac{\alpha_{x_j y_j | x_k}(t)\ 0_{x_k y.}(t)\ n_{x_k y.}(t)}{\sum_{x_k=x_1}^{x_c} 0_{x_k y.}(t)\ n_{x_k y.}(t)}.$$

If $0_{x_k y.}(t)$ is exactly the same for every location x_k at every time t, then equation (4.13) can be simplified to give:

$$(4.14) \qquad q_{x_j y_j | x_k}(t) = \alpha_{x_j y_j | x_k}(t)\ n_{x_k y.}(t) \ / \ n_{x.y.}(t).$$

Equation (4.14) states that the conditional probability of moving to location x_k from location x_j and occupation y_j is proportional to the fraction of persons in the system who are in location x_k.

This postulate is not new: the population size of a destination has long been included as a variable in models of human migration. Furthermore, in modifying Lowry's (1966) regression model of the differential attraction of migrants to metropolitan areas, Morrison (1970) specifically included size of the labor force at the destination as an independent variable explaining the conditional probability of moving from one geographical location to another.

In the present study $q_{x_j y_j | x_k}(t)$ and equations (4.9) and (4.14) are not discussed further. Although a thorough understanding of job mobility necessitates an understanding of geographical as well as occupational and industrial mobility, the data used in this study were not gathered by a sampling technique appropriate for investigating $q_{x_j y_j | x_k}(t)$ (cf. Section 5.4 below for an explanation). Consequently the remainder of the discussion of conditional transition probabilities

focuses on $q_{x_j y_j x_k | y_k}(t)$ as expressed in equation (4.10).

Equation (4.10) can also be transformed into a more common form through an assumption analogous to that used to convert equation (4.9) into equation (4.14). Let $n_{x_k y_k}(t)$ represent the actual number of persons in the system in location x_k and occupation y_k at time t, and let $0_{x_k y_k}(t)$ represent the crude or overall vacancy rate of occupation y_k in location x_k at time t. If $0_{x_k y_k}(t)$ is exactly the same for every occupation y_k in location x_k at every time t, then equation (4.10) can be reduced to the following expression:

$$(4.15) \qquad q_{x_j y_j x_k | y_k}(t) = \alpha_{x_j y_j x_k | y_k}(t)\, n_{x_k y_k}(t) \,/\, n_{x_k y.}(t).$$

This equation states that the conditional probability of entering a job in occupation y_k, given that the individual moves from location x_j and occupation y_j to location x_k, is proportional to the fraction of persons in location x_k who are in occupation y_k. Equation (4.15) is also not particularly novel as Matras (1960, 1961, 1967) incorporated the occupational distribution of the social system into a Markov chain model of intergenerational occupational mobility.

At present the practical problems entailed in determining the number of vacancies by direct methods, e.g., enumeration of vacancies in a census or sample of jobs, often leave apparently no alternative to the approximation represented by equation (4.15). If, as I expect, the crude vacancy rate $0_{x_k y_k}(t)$ varies considerably with occupation in a given location x_k, then equation (4.15) is a poor approximation to equation (4.10), although preferable to ignoring entirely the structural constraints imposed upon $q_{x_j y_j x_k | y_k}(t)$ by the distribution of vacancies

in location x_k.

Using other information to estimate $v_{x_k y_k}(t)$, which is identical to $v_k(t)$, provides an alternative to using equation (4.15). Let $l_k(t)$ represent the number of positions in state k vacated or left at time t; let $g_k(t)$ represent the net number of vacant positions in state k created at time t; and let $w_k(t)$ represent the number of positions in state k vacated at time $u < t$ that have not yet been filled. Then

$$(4.16) \qquad v_k(t) = O_k(t)\, n_k(t) = l_k(t) + g_k(t) + w_k(t).$$

Thus $v_k(t)$ can be calculated from $l_k(t)$, $g_k(t)$, and $w_k(t)$ if these quantities are known or can be estimated. For the purpose of the present exposition I assume that $w_k(t)$ is always zero, i.e., that all vacancies are immediately filled. Under this condition equation (4.16) implies that

$$(4.17) \qquad O_k(t) = l_k(t)/n_k(t) + g_k(t)/n_k(t)$$

and

$$(4.18) \qquad g_k(t) = dn_k(t)/dt.$$

Ordinarily the quantity $(dn_k(t)/dt)/n_k(t)$ is termed the growth rate of state k. If $n_k(t)$ is measured at relatively frequent time intervals, then the growth rate of state k, which equals $g_k(t)/n_k(t)$ under my assumptions, can be estimated from the slope of the plot of $n_k(t)$ versus time t. While the growth rate of state k in the future is unknown, it may be useful to extrapolate the past growth rate into the future for purposes of short-term prediction or to try other values for $g_k(t)/n_k(t)$.

The number of positions in state k which are left at time t, $l_k(t)$, can be estimated by several methods. The most direct method

is to enumerate in a population census or sample the individuals who left a position in state k during a small interval of time around time t. If one knows the instantaneous rate of leaving state k at time t, duration u, and age z, $h_k(t,u,z)$, and if one also knows the age-duration structure of the population in state k at time t, then a second method is to compute $l_k(t)/n_k(t)$ in the same manner that demographers compute a crude death rate from age-specific death rates and the age structure of a population. One can obtain information on $h_k(t,u,z)$ through the design given in Section 5.3 below and on the age-duration structure of state k by enumerating the individuals in state k at time t who are age z and have spent duration u in state k.

The two methods described above have a common disadvantage: in order to estimate $l_k(t)$, some information must be gathered at time t through either a population census or sample. Neither method permits $l_k(t)$ to be predicted from information gathered before or after time t.

A third method of estimating $l_k(t)$ overcomes this disadvantage by making certain assumptions about the mobility process which permit one to write a general expression for $l_k(t)$. The first assumption is that individuals entering and leaving positions in state k belong to a homogeneous population. The second assumption is that every position in state k is filled at the same moment that it is vacated or created, implying that $w_k(t)$ is zero, as mentioned earlier. The third assumption is that the instantaneous rate of leaving state k depends on duration u, but not on calendar time t or the individual's age z, so that the expected density of leavers after duration u is $\bar{f}_k(u)$.[6]

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[6] In general the findings of this research support the assumption that the instantaneous rate of leaving a job depends on duration but not on calendar time or the jobholder's age (cf. Section 6.2c below).

If $\bar{b}_k(t)$ is the expected density of leavers at time t for those in state k at time 0, then the expected number of leavers at time t is

$$(4.19) \qquad \bar{l}_k(t) = n_k(0)\ \bar{b}_k(t) + \int_0^t \bar{f}_k(t-z)\ v_k(z)\ dz$$

(cf. Cox, 1962; Bartholomew, 1967). Ordinarily $\bar{b}_k(t)$ and $\bar{f}_k(t)$ differ unless duration u is zero for all $n_k(0)$ persons in state k at time t.

Substituting equation (4.16) into equation (4.19) and approximating $\bar{l}_k(t)$ by $l_k(t)$, one obtains:

$$(4.20) \qquad l_k(t) = n_k(0)\ \bar{b}_k(t) + \int_0^t \bar{f}_k(t-z)\ [l_k(z) + g_k(z)]\ dz.$$

Using Laplace transforms,[7] equation (4.20) becomes:

$$(4.21) \qquad l_k^{\dagger}(s) = n_k(0)\ \bar{b}_k^{\dagger}(s) + \bar{f}_k^{\dagger}(s)\ l_k^{\dagger}(s) + \bar{f}_k^{\dagger}(s)\ g_k^{\dagger}(s),$$

where $l_k^{\dagger}(s)$ represents the Laplace transform of $l_k(t)$, and so forth. If $\bar{b}_k(t)$, $\bar{f}_k(t)$, and $g_k(t)$ are known and their Laplace transforms exist, then equation (4.21) can be solved in terms of $l_k^{\dagger}(s)$. If $l_k^{\dagger}(s)$ can be inverted, then one can obtain an expression for $l_k(t)$.

For example, suppose that state k grows at a constant rate γ:

$$(4.22) \qquad g_k(t) = \frac{dn_k(t)}{dt} = \gamma\ n_k(t),$$

which implies that

$$(4.23) \qquad n_k(t) = n_k(0)\ \exp[\gamma t],$$

and therefore that

$$(4.24) \qquad g_k(t) = \gamma\ n_k(0)\ \exp[\gamma t].$$

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[7] Since Laplace transforms are discussed in many works (e.g., cf. Smith, 1966), I am assuming some familiarity with them.

Suppose also that

$$(4.25) \qquad \bar{b}_k(t) = \bar{f}_k(t) = \kappa \exp[\kappa t],$$

which is exactly equation (2.12) of Probability Law I. It can then be shown that

$$(4.26) \qquad l_k(t) = \kappa\, n_k(0) \exp[\gamma t].$$

Substituting equations (4.24) and (4.26) into equation (4.16) yields:

$$(4.27) \qquad v_k(t) = (\kappa + \gamma)\, n_k(0) \exp[\gamma t],$$

which implies that

$$(4.28) \qquad o_k(t) = v_k(t)/n_k(t) = \kappa + \gamma.$$

On the other hand, if one assumes that

$$(4.29) \qquad \bar{b}_k(t) = \bar{f}_k(t) = \beta\lambda_1 \exp[-\lambda_1 t] + (1 - \beta)\lambda_2 \exp[-\lambda_2 t],$$

which is identical to equation (2.72) of Probability Law v, then it can be demonstrated that

$$(4.30) \qquad l_k(t) = \frac{n_k(0)}{\mu} \exp[\gamma t] + \frac{a\, n_k(0)}{b + \gamma} (b \exp[-bt] + \gamma \exp[\gamma t]),$$

where

$$(4.31) \qquad b = \beta\lambda_2 + (1 - \beta)\lambda_1,$$

$$(4.32) \qquad \mu = b/\lambda_1\lambda_2,$$

and

$$(4.33) \qquad a = \beta\lambda_1 + (1 - \beta)\lambda_2 - 1/\mu.$$

Equations (4.17), (4.24), and (4.30) imply that

$$(4.34) \qquad 0_k(t) = 1/\mu + \gamma + \frac{a + a\,b\,\exp[-(b+\gamma)t]}{b+\gamma}.$$

This search for ways to estimate $v_{x_k y_k}(t)$ and $0_{x_k y_k}(t)$ arose from the lack of direct measurements of the number of vacancies in jobs in different occupations and locations in previous years and my dissatisfaction with the assumption that $0_{x_k y_k}(t)$ is independent of occupation y_k for a given location x_k, and consequently with the approximation to equation (4.10) represented by equation (4.15). Unfortunately, $v_{x_k y_k}(t)$ can not be estimated for every occupation in a given location using any of the three methods discussed above with the data available in this research. Thus, equation (4.15) cannot be entirely avoided. However, equations (4.28) and (4.34) can be used to estimate values of $0_{x_k y_k}(t)$ for groups of equivalent respondents in selected occupations and locations. The extent of variation in the crude vacancy rates in a given location, and hence the validity of equation (4.15), can be crudely assessed by comparing these values.

4.3 The identification of equivalent social positions

Whether equation (4.10) or (4.15) is used, note that an alteration in the categorization of positions generally changes $v_{x_k y_k}(t)$ and $n_{x_k y_k}(t)$, and consequently $q_{x_j y_j x_k | y_k}(t)$. For example, suppose that location x_k has a thousand vacant positions, one hundred of which are in occupation y_k. According to equation (4.10),

$$(4.35) \qquad q_{x_j y_j x_k | y_k}(t) = 0.1\, \alpha_{x_j y_j x_k | y_k}(t).$$

If the one hundred vacant positions in occupation y_k are equivalent but arbitrarily subdivided into two categories y_{k_1} and y_{k_2} containing sixty

and forty vacancies, respectively, then

$$q_{x_j y_j x_k | y_{k_1}}(t) = 0.06\, \alpha_{x_j y_j x_k | y_k}(t) \tag{4.36}$$

and

$$q_{x_j y_j x_k | y_{k_2}}(t) = 0.04\, \alpha_{x_j y_j x_k | y_k}(t). \tag{4.37}$$

Thus, although positions in y_k, y_{k_1}, and y_{k_2} are equivalent and have the same attraction $\alpha_{x_j y_j x_k | y_k}(t)$,

$$q_{x_j y_j x_k | y_k}(t) > q_{x_j y_j x_k | y_{k_1}}(t) > q_{x_j y_j x_k | y_{k_2}}(t) \tag{4.38}$$

because

$$v_{x_k y_k}(t) > v_{x_k y_{k_1}}(t) > v_{x_k y_{k_2}}(t). \tag{4.39}$$

In other words, when finer distinctions in categorizing positions reduce the number of vacancies in the states of the system, the magnitude of conditional transition probabilities is also reduced.

As a consequence of this, one cannot decide whether jobs in different occupations and locations are equivalent destinations by comparing conditional transition probabilities directly. Instead one must compare values of the attraction of destinations with various attributes so that the sociological similarities and differences of destinations are not masked by differences in the number of vacancies. Rearranging equation (4.10), we obtain:

$$\alpha_{x_j y_j x_k | y_k}(t) = q_{x_j y_j x_k | y_k}(t)\, v_{x_k y.}(t) \,/\, v_{x_k y_k}(t), \tag{4.40}$$

and rearranging equation (4.15),

$$(4.41) \qquad \alpha_{x_j y_j x_k | y_k}(t) = q_{x_j y_j x_k | y_k}(t)\, n_{x_k y.}(t) \,/\, n_{x_k y_k}(t).$$

If one estimates $q_{x_j y_j x_k | y_k}(t)$ as the observed proportion of transitions from location x_j and occupation y_j to location x_k that have occupation y_k for the destination, then $\alpha_{x_j y_j x_j | y_k}(t)$ can be estimated from equation (4.40) when one can estimate $v_{x_k y_k}(t)$, or from equation (4.41) when one can only estimate $n_{x_k y_k}(t)$.

An explanation of the magnitude of $\alpha_{x_j y_j x_k | y_k}(t)$, the subject of the remainder of this chapter, should be based on the fact that except for those who become self-employed, individuals not only choose but are chosen for a new job. Both an individual about to enter a new position and an employer about to hire a new employee presumably select the most satisfactory situation (position or employee) of those he perceives to be available to him. The fundamental structural constraint on the choice is the number of prospective situations (vacant jobs or job-seekers) of different types at the time of the choice. However, the chooser does not obtain information on prospective situations without some cost in time and other social rewards. As a consequence of the cost of search activities, the chooser actually evaluates only a small proportion of the total number of prospective situations which he could consider. Furthermore, the distribution of the types of prospective situations that the chooser evaluates is generally not representative of all situations available at that time. In order to minimize the cost of search activities and to maximize his future satisfaction, the chooser presumably narrows his search to the most desirable types of situations that he expects can be attained at a reasonable cost.

In general deviations in $\alpha_{x_j y_j x_k | y_k}(t)$ from the value of 1.0 predicted by the pure random sampling model should depend on the desirability of the destination to the job-seeker, the desirability of the job-seeker to the employer, the job-seeker's knowledge of vacancies with various attributes, and the employer's knowledge of job-seekers with various personal characteristics. Unfortunately the data available in the present study do not permit the chooser's information on prospective situations to be distinguished from his preference for particular situations, or even a man choosing a new job to be distinguished from an employer choosing a new employee. I am only able to detect associations between attributes of individuals and attributes of positions as manifested in the magnitude of $\alpha_{x_j y_j x_k | y_k}(t)$. Nevertheless, there are reasons, which I indicate below, for thinking that certain variables on which I have data influence $\alpha_{x_j y_j x_k | y_k}(t)$. With regard to the problem of identifying equivalent social positions, I discuss and investigate the effect on $\alpha_{x_j y_j x_k | y_k}(t)$ of the location and occupation[8] of the destination k and the location, occupation, and industry of the origin j.

Occupational classification is one of the most important job attributes affecting the desirability of a job to a job-seeker. Occupation not only specifies the nature of the work required in a job but also delimits to a considerable extent the level of various rewards (money, prestige, leisure, etc.) that can be anticipated in such a job.

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[8] In this research I could differentiate the destination k on the basis of either occupation or industry (cf. Section 5.4 for an explanation). I have chosen the former as it seems much more pertinent than the latter to the process of an individual entering a new job.

I expect individuals varying widely in fixed personal characteristics, e.g., educational level, and to a lesser extent even in their previous work experience, to show a high degree of congruency in rating the desirability of jobs in different occupations. For example, most individuals rate unemployment as one of the least desirable destinations and jobs in white collar work as among the most desirable destinations. Hence individuals tend to compete for the more desirable positions on the basis of their desirability as employees. Furthermore, employers tend to agree considerably in ranking the desirability of potential employees varying in fixed personal attributes, e.g., educational level. Consequently employers usually hire job-seekers who are generally considered more desirable employees for the positions which job-seekers generally consider more desirable destinations. Thus, for a homogeneous subpopulation moving from location x_j to location x_k, I expect to find occupations y_1, y_2, and y_3 that job-seekers desire or prefer in the order $y_1 > y_2 > y_3$ such that

$$(4.42) \qquad \alpha_{x_j y.x_k|y_1}(t) < \alpha_{x_j y.x_k|y_2}(t)$$

and

$$(4.43) \qquad \alpha_{x_j y.x_k|y_2}(t) > \alpha_{x_j y.x_k|y_3}(t).$$

Equation (4.42) results from employers filling most job vacancies in occupation y_1 with individuals whom they consider more desirable employees than the members of the given subpopulation; equation (4.43) follows from most members of this subpopulation finding jobs in occupations that they consider more desirable than occupation y_3.

Geographical location of the destination x_k, given that x_j is the location of the origin, ordinarily affects $q_{x_j y_j x_k | y_k}(t)$ through its influence on the distribution of vacancies, but this does not necessarily imply that $\alpha_{x_j y_j x_k | y_k}(t)$ varies with location x_k. Variations with location in the desirability of different occupations to job-seekers and in the desirability of job-seekers with various attributes to employers could cause $\alpha_{x_j y_j x_k | y_k}(t)$ to vary with location x_k, but such variations should usually be slight. Location of the destination could also affect $\alpha_{x_j y_j x_k | y_k}(t)$ through its influence on the supply of job-seekers with attributes desired by employers, but this supply should be highly correlated with the proportion of vacancies in unemployment, i.e., the unemployment rate, which greatly reduces the independent effect of location x_k on $\alpha_{x_j y_j x_k | y_k}(t)$ through such an influence. Finally, the location of the destination may affect $\alpha_{x_j y_j x_k | y_k}(t)$ through its influence on a job-seeker's knowledge of the most desirable types of jobs that he can obtain at a reasonable cost. In particular, most individuals moving from location x_j to a new location x_k are probably hindered in searching for a job and eventually enter jobs in the less desirable occupations more often than would have been expected for nonmigrants. In other words, I expect $\alpha_{x_j y_j x_k | y_k}(t)$ to differ in magnitude from $\alpha_{x_j y_j x_j | y_k}(t)$, the former tending to be larger than the latter for the least desirable occupations and smaller than the latter for the most desirable occupations.

Since the argument in the preceding paragraph centers on the relation of the location of the destination to the location of the origin, the same argument also applies to the effect on $\alpha_{x_j y_j x_k | y_k}(t)$ of the location of the origin x_j, given that x_k is the location of the

destination. Consequently, I expect $\alpha_{x_j y_j x_k | y_k}(t)$ to differ in magnitude from $\alpha_{x_k y_k x_k | y_k}(t)$, the former tending to be larger than the latter for the least desirable occupations and smaller than the latter for the most desirable occupations.

Occupational classification of the origin y_j should strongly affect $\alpha_{x_j y_j x_k | y_k}(t)$. Employers usually prefer to hire individuals with experience in the same occupation as that of the vacancy to be filled. Moreover those with experience in a particular occupation are more likely than those without such experience to perceive a job in this occupation as satisfactory, to be well-informed about job vacancies in this occupation, and therefore to search for a job in this occupation. Therefore I expect individuals leaving occupation y_j to have an increased likelihood of a transition to a destination in the same occupation, that is,

$$\alpha_{x_j y_j x_k | y_j}(t) > \alpha_{x_j y_j x_k | y_k}(t), \tag{4.44}$$

where $y_j \neq y_k$.

On the other hand, I do not expect industrial classification of a job in occupation y_j to affect $\alpha_{x_j y_j x_k | y_k}(t)$ significantly, unless occupational skills and rewards vary considerably with industry. Industrial classification per se would not seem to influence the desirability of a job to a job-seeker, the desirability of a job-seeker to the employer, the job-seeker's knowledge of job vacancies, or the employer's knowledge of job applicants. This hypothesis is supported by Reynold's (1952) conclusions that the industrial ties of manual workers are quite loose and that the influence of industry upon mobility primarily results from variation in occupational opportunities with industry.

4.4 The identification of equivalent individuals

In this study I examine the effect of three attributes of an individual that are fixed throughout his work history: educational level, the primary location in which he was reared, and migrant farm background. Of these variables, only educational level should significantly influence $\alpha_{x_j y_j x_k | y_k}(t)$, and therefore $q_{x_j y_j x_k | y_k}(t)$.

As I mentioned in the previous section, the desirability of jobs in a particular occupation y_k, as perceived by individuals moving from location x_j and occupation y_j to location x_k, should vary only slightly with fixed personal attributes such as educational level, the location reared, and migrant farm background. Thus if individuals varying in these characteritics rank the desirability of jobs in different occupations for a given location, I expect the differences in their response to be nearly random.

But a job-seeker is usually sensitive to the demand for workers with his particular attributes. If he perceives that employers filling vacancies in the more desirable occupations consider him a desirable employee, then he is more likely to search and be hired for one of these jobs. It is, of course, well-known that employers evaluate a potential employee on the basis of his personal attributes, and of the three characteristics considered here, especially his educational level. In order to obtain satisfactory work performance, most employers prefer to hire someone with more than a certain minimum level of education; in order to obtain a worker satisfied with his job, employers sometimes prefer also to hire someone with less than a certain maximum level of education. In general, I expect individuals with higher levels of education to be more likely to enter the more desirable jobs

and those with lower levels of education to be more likely to enter the less desirable jobs.

Neither the location in which the individual was reared nor migrant farm background probably enter directly into the employer's rating of a potential employee. But in this study of Mexican-American men, the location reared may serve as an indicator of English language ability and of United States citizenship, both of which often affect an employer's evaluation of a job applicant. If this is the case, employers filling vacancies in more desirable occupations may preferentially hire men reared in Michigan rather than those reared in Texas, and the latter rather than those reared in Mexico. Such an indirect effect of the location reared should be much less important than the direct effect of educational level.

4.5 The correspondence between the theoretical construct time t and observable measures of time

In this study I investigate the effect of three observable measures of time: calendar time, an individual's age, and his duration in state j. While $\alpha_{x_j y_j x_k | y_k}(t)$, and therefore $q_{x_j y_j x_k | y_k}(t)$ probably depend somewhat on all three measures of time, I do not expect the effect of these three variables on $\alpha_{x_j y_j x_k | y_k}(t)$ to be as marked and as unambiguous as the effect of the occupation and location of the destination and origin, and of the educational level of the job-seeker.

Calendar time ordinarily affects $q_{x_j y_j x_k | y_k}(t)$ because the distribution of job vacancies in different occupations fluctuates with this measure of time, and for this reason the theoretical construct time t must be conceptualized as calendar time rather than an individual's age or his duration in state j, which do not affect the

distribution of vacancies in the system. But this does not necessarily imply that calendar time affects $\alpha_{x_j y_j x_k | y_k}(t)$.

Although it is reasonable to expect $\alpha_{x_j y_j x_k | y_k}(t)$ to depend on calendar time, predicting the nature of this dependency is exceedingly difficult because the effect of calendar time results from the dependence of $\alpha_{x_j y_j x_k | y_k}(t)$ on properties of the social system that change with calendar time in a complex fashion. In particular, fluctuations in the supply of job-seekers with different attributes accompany changes in the level of economic activity with calendar time. With an increase in the supply of job-seekers possessing characteristics most desired by employers, a job-seeker is more likely to search for and accept a position in a less desirable occupation. Changes in the proportion of vacancies in unemployment, i.e., the unemployment rate, reflect to some extent changes in the supply of job-seekers with different attributes, and to this extent reduce the effect of calendar time on $\alpha_{x_j y_j x_k | y_k}(t)$.

An individual's age at the moment of the transition should also influence $\alpha_{x_j y_j x_k | y_k}(t)$, but a general tendency is not easily predicted. Both the desirability of different occupations to job-seekers and the desirability of different job-seekers to employers probably vary with the age of the job-seeker, but it is not obvious that the matching of the preferences of job-seekers and employers produces any simple pattern. Older job-seekers are likely to emphasize opportunities for advancement less and security and the physical demands of a job more than younger persons. On the other hand, employers may consider older job-applicants as more prone to absence from work due to illness than younger ones, but very young individuals as more prone to quit work

after a brief duration than older persons. Consequently, employers may prefer to hire individuals intermediate in age.

The duration that an individual spent in the previous state j may also affect $\alpha_{x_j y_j x_k | y_k}(t)$. Both the desirability of occupational destination y_j to a job-seeker and the desirability of a job-seeker to an employer filling a job vacancy in occupation y_j should be positively correlated with the length of the duration which the job-seeker spent in origin j. Therefore I expect $\alpha_{x_j y_j x_k | y_j}(t)$ to increase with the length of the duration in occupational origin j.

4.6 The validity of the Markov assumption

Do events occurring after an individual enters the labor market, and in particular his previous work and residence experiences, affect $\alpha_{x_j y_j x_k | y_k}(t)$ and hence $q_{x_j y_j x_k | y_k}(t)$? An affirmative answer to this question implies that job mobility is not a first order Markov process.

In Section 4.3 I argued that the attraction of occupational destination y_j, given that y_j is also the occupational origin, should be greater than the attraction of any other occupational destination $y_k \neq y_j$. My argument was based on the presupposition that employers usually prefer to hire persons with previous experience in the occupation of the vacancy being filled, and that individuals with experience in a given occupation are more likely than those without such experience to perceive a job in this occupation as satisfactory, to be well-informed about job vacancies in this occupation, and therefore to search for such jobs. However, I predicted that the industrial classification of the origin would not ordinarily influence an individual's attraction to different occupational destinations. Finally, I suggested that geographical location of the position being left would affect the

attraction of different occupational destinations, primarily through an effect on the job-seeker's knowledge of job opportunities in the location of the destination.

Since I predicted that the industry of the origin j would not significantly affect the attraction of different occupational destinations, I also do not expect industrial experiences in the more remote past to affect the attraction of different occupational destinations. On the other hand, previous occupational experiences should have a lingering effect both on the desirability of different occupational destinations to a job-seeker and on the desirability of a job-seeker to an employer filling a vacancy in a particular occupation. Consequently, if y_i, y_j, and y_k are the occupational classifications of positions i, j, and k consecutively held by an individual, then I expect

$$(4.45) \qquad \alpha_{y_k x_j y_j x_k | y_k}(t) > \alpha_{y_i x_j y_j x_k | y_k}(t),$$

where $y_i \neq y_k$. This is, of course, a prediction that job mobility is not a first order Markov process.

Does experience in location x_i prior to location x_j also affect the attraction of occupational destination y_k? If, as I suggested, geographical location affects the attraction of different occupational destinations primarily through an influence on the job-seeker's knowledge of job opportunities, then the effect of previous residence experiences should attenuate rapidly and lack significance unless $x_j \neq x_k$. While continuing residence in the location of the destination x_k should most favor entry into jobs in the more desirable occupations, immigrants to x_k from x_j should enter jobs in the more desirable occupations more often if location $x_i = x_k$ than if $x_i \neq x_k$.

CHAPTER 5

The Research Design

This chapter recounts the methods used in the empirical portion of this research. In the first section I report the way in which the data were collected, edited, and coded and in the second briefly examine selected characteristics of the respondents whose employment-residence histories were analyzed. The third and fourth sections describe the procedures used to investigate the issues discussed in Chapters 3 and 4, respectively.

5.1 Collection, editing, and coding of the data

The data used in this research were gathered under the direction of Harvey M. Choldin and Grafton D. Trout (1969) as part of a study of settled Mexican-Americans in seventeen Michigan counties.

The sampling technique called "controlled selection sampling" (cf. Goodman and Kish, 1950) was used to produce a probability sample of the Mexican-American population in the seventeen Michigan counties, excluding the Detroit SMSA, estimated to have at least 100 Mexican-American families. These counties, containing virtually all of the Mexican-American population in Michigan outside the Detroit SMSA, lie in the southern half of the Lower Peninsula of Michigan. Those four of the seventeen counties estimated to have more than 800 Mexican-American families were selected with certainty. The remaining

thirteen counties were assigned to three strata homogeneous with respect to the presence or absence of a large city in the county and with approximately the same estimated number of settled Mexican-Americans. The selection process also controlled the geographical distribution of the sample (the location of the county in the eastern, central, or western part of the state). One county was selected from each stratum with a probability proportionate to the estimated number of settled Mexican-American families in the county. For one of the counties selected, the estimated number of Mexican-American families was so low that in order to obtain an overall sampling rate consistent with the other counties, it was necessary either to double-weight a subsample of them or to select a second sample county from the same stratum and to represent that stratum by a probability selection of two counties rather than by one. The research directors chose the latter course, but they picked the second county from the stratum on the basis of personal judgment and thus departed from a strict probability selection design.

For each of the eight counties selected, lists of names and addresses of known Mexican-American residents and others with Spanish surnames were compiled using assorted published lists as well as informants in contact with Mexican-Americans. A pilot study indicated that the two major errors in the lists were nonlocatable addresses and the inclusion of names of non-Mexican-Americans. Having a goal of about 850 interviews and estimating attrition of the sample at about fifty percent, the investigators decided on an overall sampling rate of 18.2 percent. Thus the sample was drawn by taking 18.2 percent of the names listed for a county multiplied by a weighting factor (1.0 for the

four counties selected with certainty; the ratio of the estimated number of Mexican-Americans in the stratum to the estimated number in the county for the four counties chosen under the controlled selection technique). This procedure yielded 1707 names.

Bilingual and biliterate Mexican-American residents of the selected counties were trained as interviewers. They attempted to interview the 898 heads of Mexican-American households in the sample who were located (about 53 percent of the sample) and successfully completed interviews with 695 persons (about 41 percent of the sample).

As I wanted information on a relatively homogeneous population, I eliminated from my analysis interviews of persons differing sharply from the majority: 32 males with more than a high school education and 69 females. In addition I removed the interviews of ten other males whose interviews were seriously incomplete for the purpose of my analysis. This left interviews of 584 Mexican-American male heads of household with twelve or fewer years of completed schooling (hereafter referred to as "the respondents") as the data for my research.

The lengthy interview schedules contain information on the employment and residence history of each respondent from age sixteen to the time of his interview, as well as extensive information on his background and current situation. Only a small proportion of the interview schedule, primarily the employment-residence history, was used in this research.[1] Each history consists of one or more sequences, where a new sequence begins whenever the respondent changed

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[1]Appendix A contains the four pages of the interview schedule pertaining to the employment-residence histories. The complete interview schedule is included in the report of Choldin and Trout (1969).

his residence (excluding intracity moves), occupation, or employer. The information on each sequence includes the respondent's age at the beginning of the sequence, location (city and state), occupation, the type of business of the employer, and the duration of the sequence, as well as other information not used in this study. I excluded from the analysis sequences occurring before the respondent began regular employment in the labor force, which I treated as occurring when the respondent spent a full year in nonstudent activities. This gave 4066 employment-residence sequences for the 584 respondents as the basis for my analysis. I treated each sequence as an instance of some state j. In those cases in which the respondent had both a primary and secondary occupation, I considered the primary occupation as the occupational category of state j.

The employment-residence histories proved to be the most difficult part of the interview to edit and code. Sometimes considerable editorial judgment was required to translate the information on an interview schedule into a set of objective codes in a standard format. In order to standardize the editorial process and minimize distortion of the raw data, we devised a set of rules for editing these histories (cf. Appendix B). I reviewed the initial editing of each history and made corrections whenever the editing deviated from the rules. In a few cases we relaxed the rules slightly if information in other sections of the interview schedule seemed to justify it.

In order to standardize coding, one person coded the occupation and industry for each sequence of every respondent's history. The 22 occupation and 40 condensed industry groups developed by the U.S. Bureau of the Census for the 1960 Census of Population formed the

basis for the classification used in the initial coding. However we devised additional occupation and industry codes for sequences in which the respondent was a member of the armed forces, a student, a prisoner, retired, or unemployed (temporarily out of work but not necessarily looking for work), and we distinguished between farm owner operators and farm managers (tenant farmers and sharecroppers), between craftsmen and factory foremen, and between migratory and nonmigratory farm laborers. Tables 5.1 and 5.2 contain the occupational and industrial classification schemes used along with the frequency of the categories in the respondents' histories.

After the respondents' histories had been edited, coded, and punched on cards, I performed a careful computer search for logical inconsistencies and arithmetic mistakes. I checked each inconsistency and arithmetic mistake with the original interview and corrected the errors.

The main deficiencies of these data, insofar as the present research is concerned, stem from the fact that the data were gathered retrospectively. Ideally one would sample a population at some point in time prior to entry into the labor force, and then record changes in occupation, employer, and residence for each individual beginning with his entry into his first job and ending with his permanent exit from the labor force. One would not, as we did, sample a population of individuals at intermediate and different stages of their work histories, and then ask each person to recall his employment and residence history from his sixteenth birthday to the present.

Because we could not sample prior to entry into the labor force, one cannot generalize from my findings about the work histories of

Table 5.1 Occupational classification scheme with frequency of the categories in respondents' histories.

Title	Frequency	
White collar workers	163	
Professional, technical, and kindred workers		14
Managers, officials, and proprietors, except farm		55
Clerical and kindred workers		39
Sales workers		55
Craftsmen and foremen	298	
Construction craftsmen		76
Mechanics and repairmen		72
Metal craftsmen, except mechanics		62
Other craftsmen		57
Factory foremen		31
Drivers and deliverymen	170	170
Operatives (other operatives and kindred workers)	1252	1252
Service workers	236	
Private household workers		0
Protective service workers		10
Waiters, cooks, and bartenders		44
Other service workers		182
Nonfarm laborers	622	622
Farm proprietors	51	
Farm owner operators		18
Tenant farmers and sharecroppers		10
Unpaid family farm workers[2]		23
Migratory farm laborers	513	513
Nonmigratory farm laborers	289	289
Men not in the civilian labor force	472	
Members of the armed forces		171
Students		37
Prisoners		1
Retired persons		45
Unemployed persons		218
TOTAL	4066	4066

[2] I included unpaid family farm workers with farm proprietors rather than farm laborers because the data show that they resemble the former much more closely than the latter in the mean number of years spent in a job: tenant farmers and sharecroppers (5.8 years), unpaid family farm workers (5.3), farm owner operators (5.0), nonmigratory farm laborers (4.3), and migratory farm laborers (2.9).

Table 5.2 Industrial classification scheme with frequency of the categories in respondents' histories.

Title	Frequency	
Agriculture	896	896
Other extractive industries	21	
Forestry and fisheries		3
Mining		18
Construction	356	356
Manufacturing, fabricated metals	454	454
Manufacturing, motor vehicle	453	453
Manufacturing, other durable goods	189	
Furniture, lumber, and wood products		74
Primary metal industries		7
Machinery, except electrical		2
Electrical machinery		67
Transportation equipment, except motor vehicle		15
Other durable goods		24
Manufacturing, food and kindred products	205	205
Manufacturing, other non-durable goods	116	
Textile mill products		10
Apparel and other fabricated textile products		1
Printing, publishing, and allied industries		4
Chemicals and allied products		27
Other non-durable goods		74
Transportation, communication, and utilities	205	
Railroads and railway express service		106
Trucking service and warehousing		48
Other transportation		27
Communications		2
Utilities and sanitary services		22
Trade	314	
Wholesale trade		23
Food and dairy retailing		45
Eating and drinking places		79
Other retail trade		167
Services	342	
Finance, insurance, and real estate		4
Business services		1
Repair services		70
Private households		9
Other personal services		91
Entertainment services		31
Hospitals		22
Educational services, government		2
Educational services, private		12

Table 5.2 (cont'd.)

Title		Frequency
Services (cont'd.)		
Welfare, religious and nonprofit organizations		9
Other professional and related services		12
Public administration		79
Industry not reported	43	43
Men not in the civilian labor force	472	
Members of the armed forces		171
Students		37
Prisoners		1
Retired persons		45
Unemployed persons		218
TOTAL	4066	4066

respondents with particular characteristics to others with the same characteristics who did not reside in the sample counties at the time of our interviews. This fact acts to limit the generality of my findings rather than to negate their validity.

On the other hand, gathering work histories by asking respondents to recall past events can affect the validity of the findings. Self-reporting is always subject to intentional and unintentional distortion of facts, but self-reporting on past events is particularly susceptible to errors resulting from inaccurate memories. The problem is magnified by the fact that the respondents are relatively uneducated and that interviewers were not instructed to use special care in order to obtain complete and accurate job histories.

Given the nature of the data available in this study, I was unable to devise any satisfactory method of measuring the errors resulting from self-reporting of past events. I judge that respondents reported most jobs held an appreciable length of time, but I am less confident that they reported all jobs and nonwork activities of short duration. Short-term unemployment appears to be grossly underreported. Jobs that are ill-defined, brief, and lacking in personal significance for the respondents are probably disproportionately underreported. I expect that a high proportion of such jobs would be classified as nonfarm laborer, e.g., "odd jobs" and work as handymen, or farm laborer, but I am unable to assess the effect of this on conclusions concerning these two occupations. Finally it is clear from the interviews that most respondents or interviewers rounded off the duration of sequences to some convenient figure and that rounding is generally in rough proportion to the length of the duration. The rules for editing job

histories (cf. Appendix B) were based on this premise.

5.2 Selected characteristics of the respondents

A brief examination of the distribution of the respondents on variables possibly influencing job mobility indicates the degree of homogeneity of the respondents.

Father's education and occupation are often held to influence social mobility. Although only 55 percent of the respondents supplied information on the last school year completed by their father, 51 percent of these reported that their father had no schooling and an additional 43 percent said that their father completed from one to six years of school. This suggests that the educational level of the father of most respondents is quite low. Information on the father's principal occupation while the respondent was growing up is more complete, with 93 percent furnishing this information. Most respondents answering this question fall into one of two groups of similar size: those with father in a blue collar occupation (43 percent) and those with father in a farm occupation (49 percent).

The farm-nonfarm difference is also implied by the primary location in which respondents were reared: 18, 60, and 20 percent in Michigan, Texas, and Mexico, respectively. The social milieu of the industrialized economy of Michigan differs greatly from that of the more agriculturally oriented economies of Texas and Mexico. That 55 percent reported someone in their family doing migrant farm labor before the respondent's sixteenth birthday provides further evidence of heterogeneity with regard to farm background.

Table 5.3 shows that the respondents also vary considerably in their own educational level. Distinguishing among the effects on job

mobility of educational level, the location in which the respondent was reared, and migrant farm background is complicated by a high correlation among these variables for the respondents.

Table 5.3 Respondents' educational level

Last school year completed	Percent
0-3	28
4-8	42
9-12	30
	100%
Total N =	584

Events in the marital and fertility history of an individual are also thought to affect job mobility. At the time of the interview only one percent of the respondents were single and nearly 96 percent were presently married. Unfortunately data on events in the marital and fertility history of the respondents are inadequate for studying the impact of these events on job mobility.

5.3 Investigation of the process of individuals leaving a social position

In this research empirical investigation of the process of individuals leaving a social position consists of analyzing respondents' histories in terms of the seven issues discussed in Chapter 3. This research has two main phases: (a) identifying equivalent individuals in equivalent jobs, and (b) evaluating probability laws intended to describe the process by which equivalent individuals leave equivalent jobs. The first phase investigates the issues discussed in Sections

3.2 through 3.6, the second the issue discussed in Section 3.7. The wisdom of conceptualizing a job as a state j, the subject of Section 3.1, is revealed in the overall results of the research.

(a) A design for identifying equivalent individuals in equivalent jobs

The general design that serves as the basis for investigating the issues raised in Sections 3.2 through 3.6 can be summarized as follows. Suppose that a large pool of information is available on the duration that individuals with varied attributes have spent in a variety of jobs. Let these jobs and individuals be classified on various attributes that may influence the mobility process. Then examine the data for individuals in jobs identical on every variable but one temporarily under scrutiny. For each category of this particular variable calculate quantities corresponding to any one of the four mathematical functions that define the probability law describing the leaving process, i.e., $h_j(t)$, $\overline{G}_j(t)$, $\overline{F}_j(t)$, or $\overline{f}_j(t)$. Plots of the observed values corresponding to the selected function versus duration t should differ only randomly[3] among categories of the variable if this particular variable does not affect the leaving process.

This design presupposes a relatively large quantity of data on the duration spent in equivalent jobs by equivalent individuals. Consequently it is desirable to eliminate from the analysis sequences with

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[3]Circularity can not be avoided in empirically investigating the issues discussed in Chapter 3. In order to decide which differences exceed random variation, one needs to know which probability law describes the leaving process. But in order to decide which probability law describes the leaving process, one needs to have resolved the first six issues discussed in Chapter 3. In practice one uses a procedure of introducing successive refinements.

attributes on which the number of observations is small, yet likely to introduce nonrandom variation because these attributes are expected to influence the leaving process strongly. I therefore restricted my investigation to the four occupational categories with the most observations, i.e., operatives, nonfarm laborers, migratory farm laborers, and nonmigratory farm laborers. For the same reason I limited my examination of these occupations to sequences occurring in 1935 or later, in Texas or Michigan, and to men less than fifty years of age at the beginning of the sequence.

I studied the effect of different variables by inspecting plots of $G_j(t)$, the observed proportion remaining in job j after duration t, versus duration t. Calculating values for $G_j(t)$ is not as straightforward as it may appear because the data include observations on men who had not yet left job j at the time of the interview. Since such observations form a sizeable proportion of the sequences on operatives, I did not wish to ignore this information.

Consequently I calculated $G_j(t)$ in the following way. For a given sequence x, let t_x be the duration that the individual spends in job j and let T_x be the length of time between his entry into job j and his interview. Naturally t_x is known only if $t_x \leq T_x$, i.e., if the respondent left job j before his interview. Let $n_j(t)$ represent the total number in job j for whom $T_x \geq t$, and let $l_j(u)$ represent the number who leave job j at time $u \leq t$. Then

$$(5.1) \qquad s_j(t) = n_j(t) - \sum_{u=0}^{t} l_j(u)$$

where $s_j(t)$ represents the total number who have not left job j at some $t_x \leq t$, and

(5.2) $$G_j(t) = s_j(t)/n_j(t)$$

where

(5.3) $$n_j(t) \leq n_j(0).$$

If t_{max} is the maximum duration any individual spends in job j, then $G_j(t)$ is undefined for $t > t_{max}$. The computer program employed in this research uses equation (5.2) to calculate values of $G_j(t)$, with specified variables controlled, from the raw data on sequences and then displays the values of $G_j(t)$ versus duration t in both tabular and graphical form.

Ideally one holds constant every variable but one and examines variation in plots of $G_j(t)$ versus duration t induced by this particular variable. This procedure requires a much larger quantity of data than is available on the respondents. Therefore I modified the ideal procedure as follows. (1) For each occupational category I examined plots of $G_j(t)$ versus duration t for each variable being investigated in this study. (2) For each occupational category, the variable introducing the most variation was then held constant and the effect of the remaining variables examined in the same fashion as in (1). I repeated this procedure until remaining variables appeared to have a negligible effect on the leaving process or until partitioning exhausted the supply of data. An additional economy proved to be necessary: when variables appeared to have a negligible effect, I did not ordinarily continue to examine them. Even with this modification this phase of the analysis involved the examination of hundreds of graphs.

(b) A design for evaluating probability laws

A design for evaluating a probability law intended to describe

the process of equivalent individuals leaving equivalent social positions is as follows. First estimate the parameters of the probability law from data on the duration spent in equivalent positions by equivalent individuals, and then use these parameter estimates to predict values of one of the four mathematical functions that define the probability law, i.e., $h_j(t)$, $\overline{G}_j(t)$, $\overline{F}_j(t)$, or $\overline{f}_j(t)$. To assess the probability law compare the values predicted for this function with those calculated from the data. This design does not significantly differ from those reported by most previous investigators.

The first phase of the research on the leaving process identified data that could reasonably be treated as observations of the same event, namely, of equivalent individuals leaving equivalent jobs. In the second phase I used the data on the duration spent by these seemingly equivalent individuals in equivalent jobs to estimate parameters of the probability laws being investigated. I estimated parameters both by the method of least squares and by the method of maximum likelihood.

The method of least squares consists in altering estimates of the parameters of a probability law so as to minimize S, the sum of the squares of the deviation between $G_j(t)$ and $\hat{G}_j(t)$,

$$S = \sum_{t=0}^{t_{max}} (G_j(t) - \hat{G}_j(t))^2, \tag{5.4}$$

where $G_j(t)$, the observed proportion remaining in job j, is calculated with equation (5.2) and $\hat{G}_j(t)$, the estimate of the expected proportion remaining in job j, is calculated from the parameter estimates using the equation for $\overline{G}_j(t)$ of the probability law. The computer program used in this research includes GAUSHAUS (cf. Meeter and Wolfe, 1965),

a set of FORTRAN and COMPASS subroutines which obtains estimates of parameters entering nonlineraly into a mathematical model by minimizing S, as defined by equation (5.4), through an iterative technique devised by Marquardt (1963).

The method of maximum likelihood, as is well known, selects those parameter values for which the probability density of obtaining the observed sample values is a maximum. If t_x is sometimes greater than T_x, the method of maximum likelihood consists of maximizing the value of the likelihood

$$L = \prod_{x=1}^{n_j(0)} [\hat{f}_j(t_x)]^{a_x} [\hat{G}_j(t_x)]^{(1 - a_x)}, \tag{5.5}$$

where for a given sequence x the value of a_x is one if the respondent left job j after duration $t_x \leq T_x$ and is zero otherwise (cf. Bartholomew, 1957). Maximizing the logarithm of the likelihood,

$$\ln L = \sum_{x=1}^{n_j(0)} a_x \ln \hat{f}_j(t_x) + (1 - a_x) \ln \hat{G}_j(t_x) \tag{5.6}$$

is mathematically equivalent to maximizing the likelihood L itself. Let ρ_z be the z^{th} parameter of the probability law and ν be the total number of parameters of the probability law. Then at the maximum value of the likelihood L

$$\frac{\partial \ln L}{\partial \rho_z} = 0 \tag{5.7}$$

for $z = 1, 2, \ldots, \nu$.

For Probability Law I, which has only the one independent parameter κ, equation (5.7) has an explicit solution:

$$(5.8) \qquad \kappa^* = \left[\sum_{x=1}^{n_j(0)} a_x t_x + (1 - a_x) T_x \right] / \sum_{x=1}^{n_j(0)} a_x .$$

For the other probability laws, equation (5.7) defines a set of simultaneous nonlinear equations. If one defines

$$(5.9) \qquad \$ = \sum_{z=1}^{\nu} \left[\frac{\partial \ln L}{\partial \rho_z} \right]^2 ,$$

then minimizing $\$$ through the use of GAUSHAUS gives parameter estimates satisfying equation (5.7).

Estimating parameters of a probability law, either by minimizing S as given by equation (5.4) or by minimizing $\$$ as given by equation (5.9), requires $\hat{G}_j(t)$ to be evaluated numerous times. Because the expression for $G_j(t)$ in Probability Law III contains an integral with no explicit solution (cf. equation (2.56)), estimating parameters for this particular probability law is considerably more troublesome than for the others discussed in Chapter 2. For this reason I abandoned my original goal of estimating parameters for Probability Law III and only attempted to estimate parameters for Probability Laws I, II, IV, V, VI, and VII.

The computer program used to obtain least squares and maximum likelihood estimates of parameters requires reasonable initial parameter values, except for the maximum likelihood estimate of κ of Probability Law I, κ^*, which is explicitly calculated from equation (5.8). I readily obtained the least squares parameter estimates of a probability law by using the maximum likelihood estimates as the initial parameter values. On the other hand, using the least squares estimates as initial parameter values did not always yield satisfactory maximum

likelihood estimates. If $\ln L$, as calculated from equation (5.6) with the least squares parameter estimates of the probability law, was less than $\ln L$ for Probability Law I using κ^*, $\ln L_I^*$, then using the least squares estimates as initial parameter values invariably led to maximum likelihood estimates of the parameters which reduced the probability law to Probability Law I. For example, for Probability Law V parameter β^* would converge to 1.0 or 0.0 and parameters λ_1^* and λ_2^* would converge to κ^*, while the value of $\ln L$ would simultaneously converge to $\ln L_I^*$.

Therefore a major problem in obtaining the maximum likelihood estimates of parameters was finding at least one set of parameter values for the probability law for which $\ln L$ was greater than $\ln L_I^*$. This presented no difficulties in many cases, especially when Probability Law I predicted the data very badly. Often any reasonable guess could be used as initial parameter values and the computer program would still converge to satisfactory maximum likelihood estimates of the parameters of a probability law. In other cases I obtained satisfactory initial estimates by guessing one parameter and then solving for the other parameters by equating observed values of $G_j(t)$ with the equation for $\overline{G}_j(t)$ of the probability law.

Sometimes even this approach was unsuccessful. But with one exception, if I could obtain maximum likelihood parameter estimates for either Probability Law II, IV, or V, then I could estimate the approximate numerical values of $\hat{h}_j(t)$ and $\hat{G}_j(t)$ which the maximum likelihood parameter estimates of a probability law should produce, equate these numerical values with the corresponding theoretical equation of the probability law, and solve for parameter values which would give a value of $\ln L$ for this probability law greater than $\ln L_I^*$.

But even though the initial parameter values of a probability law gave a value of $\ln L$ greater than $\ln L_I^*$, in several cases GAUSHAUS converged to maximum likelihood estimates that reduced the probability law to Probability Law I. I therefore included in the computer program a preliminary iterative search for parameter values to increase the value of $\ln L$ for the probability law. In most cases I eventually obtained improved initial estimates of parameters which GAUSHAUS could use to converge to apparently satisfactory maximum likelihood parameter estimates for the probability law.

Because equation (5.7) may not have a unique solution except for Probability Law I, I calculated values of $\ln L$ in a small region of the parameter space around the apparent maximum likelihood estimates in order to ascertain that these estimates at least identified a relative maximum of the likelihood L. If the estimates passed this test satisfactorily, then I have reported and treated them as if they are the maximum likelihood estimate of the parameters of the probability law. Either mathematical proof or empirical demonstration of the fact that these estimates are exactly the maximum likelihood parameter estimates requires further work beyond the scope of this research.

I judged the absolute adequacy of the different probability laws by visually comparing a plot of $G_j(t)$, the observed proportion remaining in job j after duration t, versus duration t with a plot of $G_j^*(t)$, the maximum likelihood estimate of the expected proportion remaining in job j after duration t, versus duration t. I evaluated the relative adequacy of the different probability laws by comparing values of $\ln L^*$ calculated from equation (5.6) using the maximum likelihood parameter estimates. Since L is the probability density of obtaining

the observed sample values assuming the parameter estimates are the true parameter values, it is reasonable to expect L^* and $\ln L^*$ to increase as the fit of a probability law improves.

I did not attempt to estimate confidence limits for parameters, or, except for Probability Law I, levels of significance of the variation between the observed data and comparable predicted values; these tasks present complicated statistical problems beyond the intent of this research. For Probability Law I, I did use a statistical test based on the conditional distribution of total time spent in job j at time t. Epstein (1960a: 85-86; 1960b) has described this test in detail and has stated that it is a "best" test of Probability Law I when Probability Law IV is the alternative hypothesis. Unfortunately this test only uses data on individuals for whom $t_x \leq T_x$.

5.4 Investigation of the process of individuals entering a new social position

In the present study empirical investigation of the process of individuals entering a new social position focuses entirely on $q_{x_j y_j x_k | y_k}(t)$, the conditional probability of individuals entering occupation y_k, given that they move to geographical location x_k from geographical location x_j and occupation y_j. I completely ignore $q_{x_j y_j | x_k}(t)$, the conditional probability of individuals entering geographical location x_k, given that (x_j, y_j) is their origin. In order to explore the latter concept one needs either retrospective histories of individuals gathered in a very large geographical area, or, preferably, prospective histories. Because the data for this study consist of retrospective histories of individuals residing in a comparatively small geographical area, it seemed impossible to make any conclusions

of value concerning $q_{x_j y_j | x_k}(t)$.

The research on $q_{x_j y_j x_k | y_k}(t)$ consists primarily of a search for equivalent job transitions, i.e., for equivalent individuals moving from equivalent origins to equivalent destinations at equivalent times, or alternatively stated, a search for those variables that make job transitions inequivalent. The general design is as follows. Suppose that a large pool of information is available on the number of transitions that various individuals make among a variety of social positions. In general the social positions include different types of jobs as well as unemployment, retirement, and being in school. Let individuals and social positions (both the origin and the destination) be classified on attributes thought to influence the process of individuals entering a new social position. Then examine the data for individuals making transitions that are identical on every variable except one temporarily being scrutinized. For each category of this particular variable, estimate the attraction of a transition to occupation y_k, given a move from location x_j and occupation y_j to location x_k, using the following equation:

$$\alpha_{x_j y_j x_k | y_k}(t) = q_{x_j y_j x_k | y_k}(t)\, v_{x_k y.}(t) \,/\, v_{x_k y_k}(t), \tag{5.10}$$

where the estimate of $q_{x_j y_j x_k | y_k}(t)$ is the observed proportion of transitions to occupation y_k, given a move from location x_j and occupation y_j to location x_k. If the particular variable being examined has no significant effect on the process of individuals entering a new social position, then $\alpha_{x_j y_j x_k | y_k}(t)$ should vary only randomly among the categories of the variable being studied.

This design presupposes a relatively large quantity of data on

equivalent transitions. Consequently it is desirable to eliminate from the analysis transitions for which the number of observations is small, yet likely to introduce nonrandom variation because they possess certain attributes strongly influencing the process of individuals entering a new job. For this reason I limited my analysis to those transitions with the origin and destination in Michigan or Texas made after 1934 by men less than fifty years old. The last restriction effectively excludes the possibility of men entering retirement.

The above design also presumes that for location x_k one can satisfactorily estimate the number of vacancies in every occupational category y_k. To date such vacancies have not been enumerated; however, I demonstrated in Section 4.2 that if the crude or overall vacancy rate of equivalent individuals leaving occupation y_k in location x_k at time t, $O_{x_k y_k}(t)$, is the same for all individuals in every occupation y_k in a given location x_k at a given time t, then

$$(5.11) \qquad \alpha_{x_j y_j x_k | y_k}(t) = q_{x_j y_j x_k | y_k}(t)\, n_{x_k y.}(t) \,/\, n_{x_k y_k}(t),$$

where $n_{x_k y_k}(t)$ is the actual number of individuals in (x_k, y_k) at time t.

At present a lack of practical alternatives compels me either to use equation (5.11) or to disregard entirely the problem of calculating values of $\alpha_{x_j y_j x_k | y_k}(t)$. Because the equivalence of different destinations and of different points in calendar time can only be determined by comparing values of $\alpha_{x_j y_j x_k | y_k}(t)$ (cf. Section 4.2), I have chosen to utilize equation (5.11) in investigating these two issues, but to compare values of $q_{x_j y_j x_k | y_k}(t)$ directly in investigating all other issues, for which equivalence can be decided without first estimating

$\alpha_{x_j y_j x_k | y_k}(t)$.

As estimates of $n_{x_k y_k}(t)$ I have used the numbers of employed males in various occupational categories in Michigan and in Texas for the years 1940, 1950, and 1960 reported in the 1960 Census of Population of the U.S. Bureau of the Census (cf. Table 5.4). The use of these estimates meant that calendar time had to be treated as a discrete variable with three categories. I have used the categories 1935-1944, 1945-1954, and 1955-1967 so that the points in time at which the data for Table 5.4 were gathered would be near the midpoint of my categories. Needless to say, fluctuations in the occupational distribution with the seasons, and even with the business cycle, are indetectable; only long-term changes are apparent. In using these estimates it was also necessary to disregard the possible effect of the industrial classification of the destination and to exclude transitions with destinations falling in the category "men not in the civilian labor force" (cf. Table 5.1). The former is probably not critical as workers generally do not choose jobs on the basis of industrial classification (cf. Reynolds, 1951). The importance of unemployment suggested by both theory and casual observation makes the latter limitation quite undesirable. However this exclusion should do little additional harm to this research as unemployment figures averaged over the time intervals used in this study would be virtually meaningless. Finally, the U.S. Bureau of the Census has not distinguished between migratory and nonmigratory farm laborers so that these categories are treated as equivalent members of the category "farm laborers."

In the ideal design described above one holds all variables but

one constant and examines variation in $\alpha_{x_j y_j x_k | y_k}(t)$ or $q_{x_j y_j x_k | y_k}(t)$ induced by this particular variable. This procedure requires a much larger quantity of data than is available on the respondents. Their histories provide information on a total of 3482 transitions and only 2244 of these fall within the limitations mentioned above. Consequently I was unable to hold constant all variables but the one being investigated. Instead I controlled those variables that a preliminary investigation indicated to be most influential. Unfortunately it was impossible to control all important variables at the same time without obtaining tables with undesirably low cell frequencies.

Table 5.4 Estimates of the number of filled positions in different occupations by year and location, for males

	Michigan			Texas		
	1940	1950	1960	1940	1950	1960
White collar workers	3829	5130	6262	4324	6150	7821
Craftsmen and foremen	2761	3821	4101	1908	3636	4229
Drivers and deliverymen	624	819	945	735	1030	1325
Operatives	2873	4282	4003	1278	2354	2748
Service workers	783	1006	1086	955	1135	1338
Nonfarm laborers	1198	1133	1048	1317	1866	1753
Farm proprietors	1410	1103	571	3562	2454	1382
Farm laborers	648	353	208	2322	1512	1005
TOTAL N in 00's	14125	17646	18224	16401	20127	21600

CHAPTER 6

The Process of Individuals Leaving a Social Position: The Identification of Equivalent Respondents and Equivalent Jobs

Findings concerning the identification of equivalent individuals in equivalent jobs can be reported and analyzed by sequentially considering either each of the four occupations investigated or each of the five issues discussed in Chapter 3. The first approach keeps close to the actual course of the research, while the second matches the order of presenting the issues in Chapter 3. Since each has distinct advantages, I first report the findings for each occupation and then summarize and analyze these findings for the issues discussed in Sections 3.2 through 3.6.

6.1 The findings by occupation

(a) Nonfarm laborers

The respondents' histories contain information on 622 jobs as a nonfarm laborer, 468 of which were begun after 1934, in Texas or Michigan, and before the jobholder was fifty years of age. Following the design described in Section 5.3a, I began by plotting survival curves[1] of nonfarm laborers for each variable being investigated (cf. Table 6.1). Initially the respondent's educational level and the location

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[1]The term survival curve refers to a plot of $G_j(t)$, the observed proportion remaining in job j after duration t, versus duration t, where $G_j(t)$ is calculated using equation (5.2).

Table 6.1 Variables examined for nonfarm laborers with categories and number of observations.

Industry	
construction	225
other	243
Geographical location	
Texas	151
Michigan	317
Educational level	
0 years of completed schooling	52
1-3	77
4-5	83
6-7	88
8	38
9-10	77
11-12	53
Location in which respondent was reared	
Mexico	53
Texas	317
Michigan	82
other	16
Migrant farm background	
no	201
yes	267
Calendar year that job began	
1935-1944	92
1945-1949	70
1950-1954	81
1955-1959	77
1960-1967	148
Respondent's age at entering the job	
16.0-24.9 years	273
25.0-49.9	195
Previous experience in same occupation	
no	229
yes, immediately before the present job	104
yes, not immediately before the present job	135
Previous experience in same industry	
no	310
yes, immediately before the present job	67
yes, not immediately before the present job	91
Number of previous sequences	
0-2	189
3 or more	279

in which he was reared introduced the most variation into the survival curves (cf. Figures 6.1 and 6.2). Considerably less variation was brought about by the respondent's age and the calendar year at the beginning of the job. The effect of all other variables was slight and seemed well within the range of random variation.

In the initial plots of survival curves by educational level I used the arbitrary categories of 0-3, 4-8, and 9-12 years of completed schooling. Because educational level appeared particularly important, I replotted the survival curves using the finer categories given in Table 6.1. This more detailed breakdown by educational level suggested that the initial categories were an apt choice: the curves for 9-10 and 11-12 years clustered at the bottom of the graph, the curves for 4-5, 6-7, and 8 years were grouped in the middle, and the curve for 1-3 years was markedly higher. The curve for 0 years deviated from this observed regularity, resembling the curves for 4-8 years more closely than the curve for 1-3 years. But since the number of observations for 0 years was rather small (52), I continued to use the initial categories of educational level: 0-3, 4-8, and 9-12 years of completed schooling.

I also investigated the suitability of the initial categories used for the calendar year that the job began: 1935-1944, 1945-1954, and 1955-1967. Initially the curves for the first two categories were virtually identical but somewhat higher than the curve for the third category. Consequently I replotted the data using the finer categories given in Table 6.1. The curves for intervals within the period 1935-1959 were extremely similar but significantly higher than the curve for 1960-1967. Therefore I used the categories 1935-1959 and

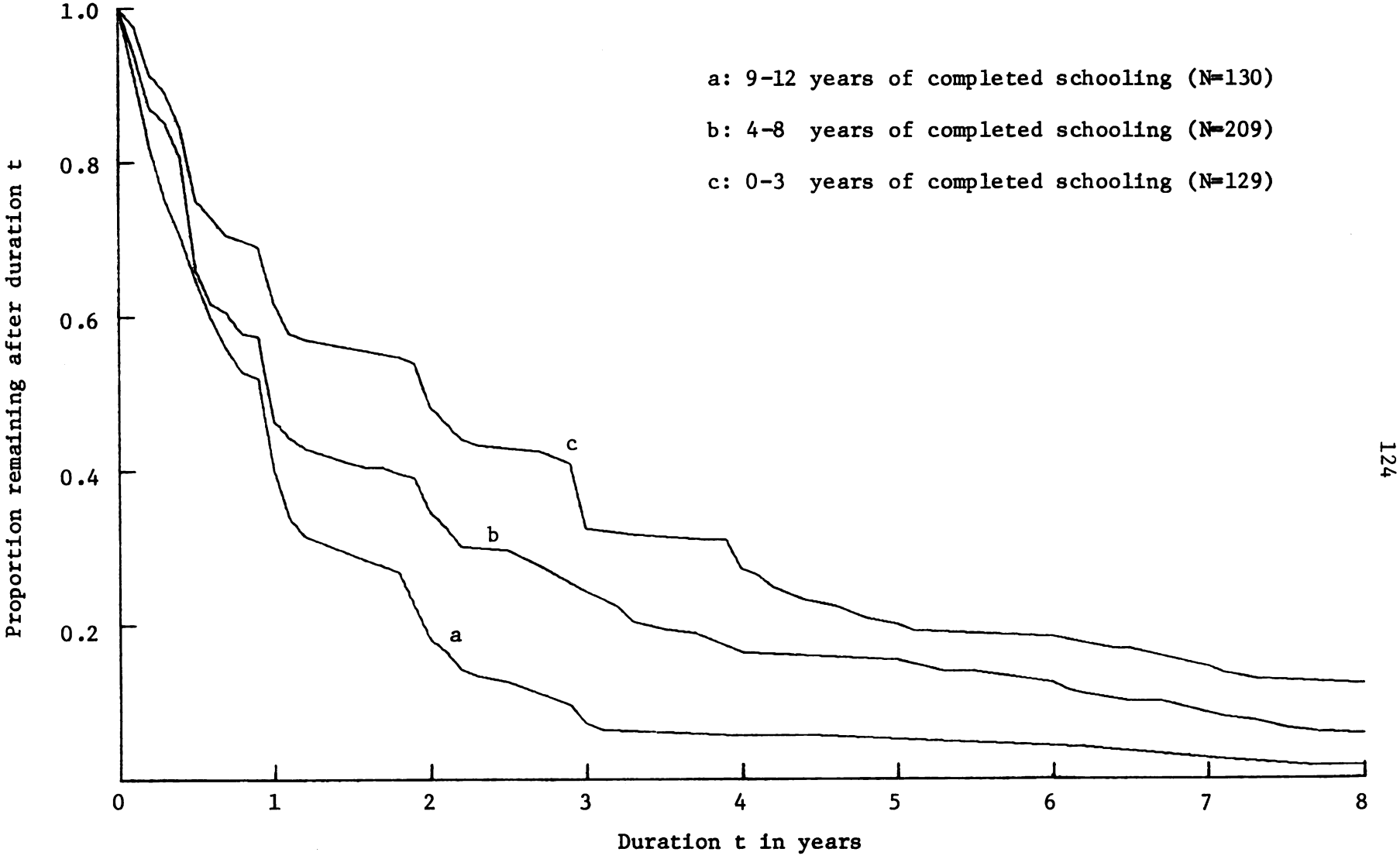

Figure 6.1 Proportion of respondents remaining in a job as a nonfarm laborer in Michigan or Texas (1935-1967) after duration t, by respondent's educational level.

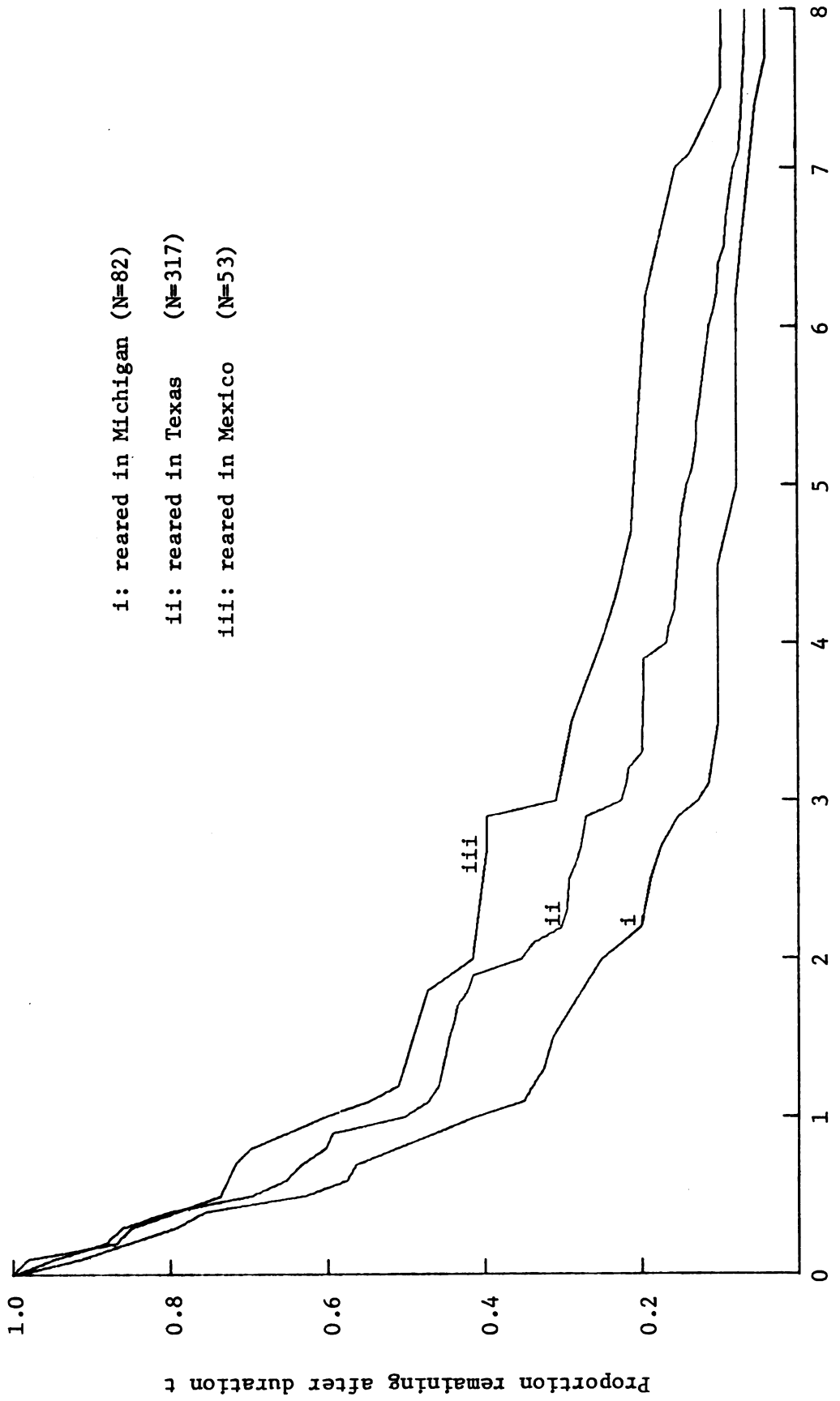

Figure 6.2 Proportion of respondents remaining in a job as a nonfarm laborer in Michigan or Texas (1935-1967) after duration t, by the location in which the respondent was reared.

1960-1967 in exploring whether the variation in the survival curves introduced by calendar year could be explained by some other variable highly correlated with it, e.g., educational level.

In accord with the design outlined in Section 5.3a, I held constant the respondent's educational level, the variable initially introducing the most variation into the survival curves, and replotted the survival curves for those variables initially causing a lesser but noticeable amount of variation. For a fixed educational level, the survival curves were only slightly affected by the location in which the respondent was reared (cf. Figure 6.3),[2] his age at entering the job, and the location of the job. However, even with educational level fixed, survival curves for 1935-1959 and 1960-1967 differed noticeably, with the latter declining much more rapidly than the former.

In analyzing this finding I became aware of a technical difficulty that arises in studying the effect of calendar year on the survival curves for any occupation. As in Chapter 5, let T_x be the length of time between the respondent's entry into sequence x and the date of his interview. If the respondent entered the sequence during 1960-1967, T_x is at most eight years, and on the average (assuming the same proportion entered job j each year) four years. This can cause $G_j(t)$ to decrease more rapidly than would normally be expected because $G_j(t)$ is calculated using equation (5.2):

$$(6.1) \qquad G_j(t) = s_j(t)/n_j(t).$$

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[2]Figures 6.1, 6.2, and 6.3 illustrate the method used in this research to determine which variables significantly affected the process of respondents leaving jobs. Including all graphs of survival curves inspected in this research is economically impractical.

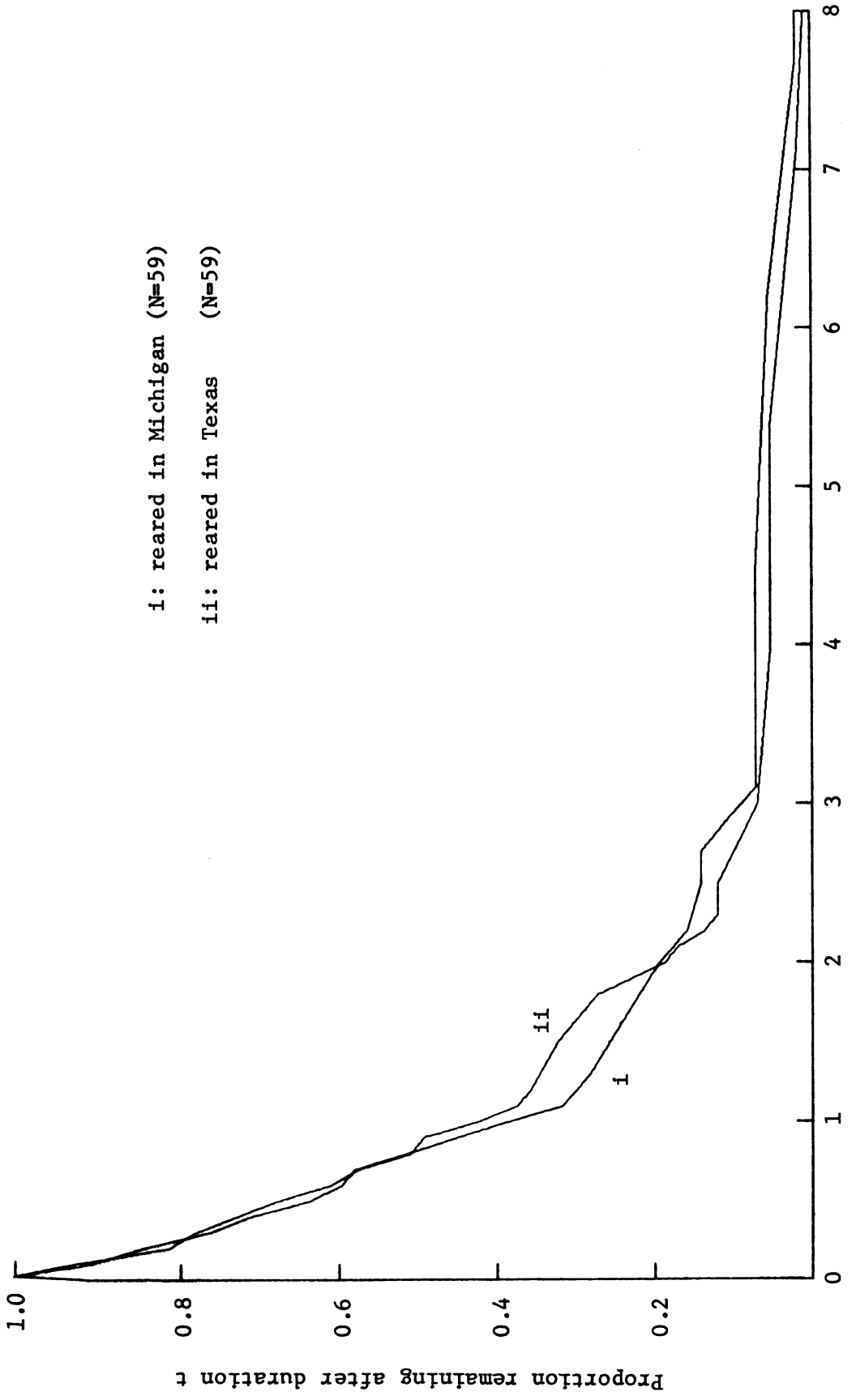

Figure 6.3 (a) Proportion of respondents with 9-12 years of completed schooling remaining in a job as a nonfarm laborer in Michigan or Texas (1935-1967) after duration t, by the location in which the respondent was reared.

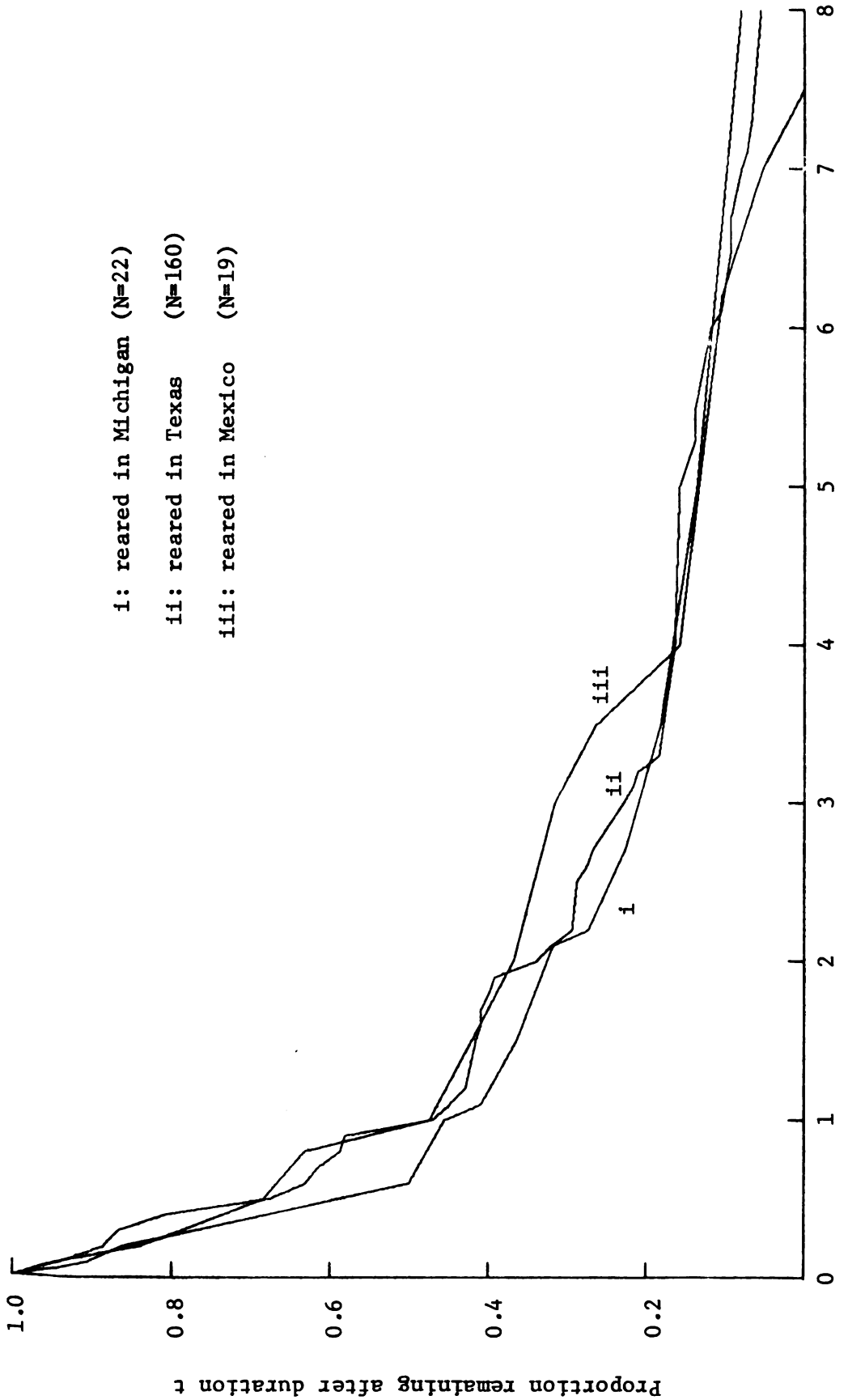

Figure 6.3 (b) Proportion of respondents with 4–8 years of completed schooling remaining in a job as a nonfarm laborer in Michigan or Texas (1935-1967) after duration t, by the location in which the respondent was reared.

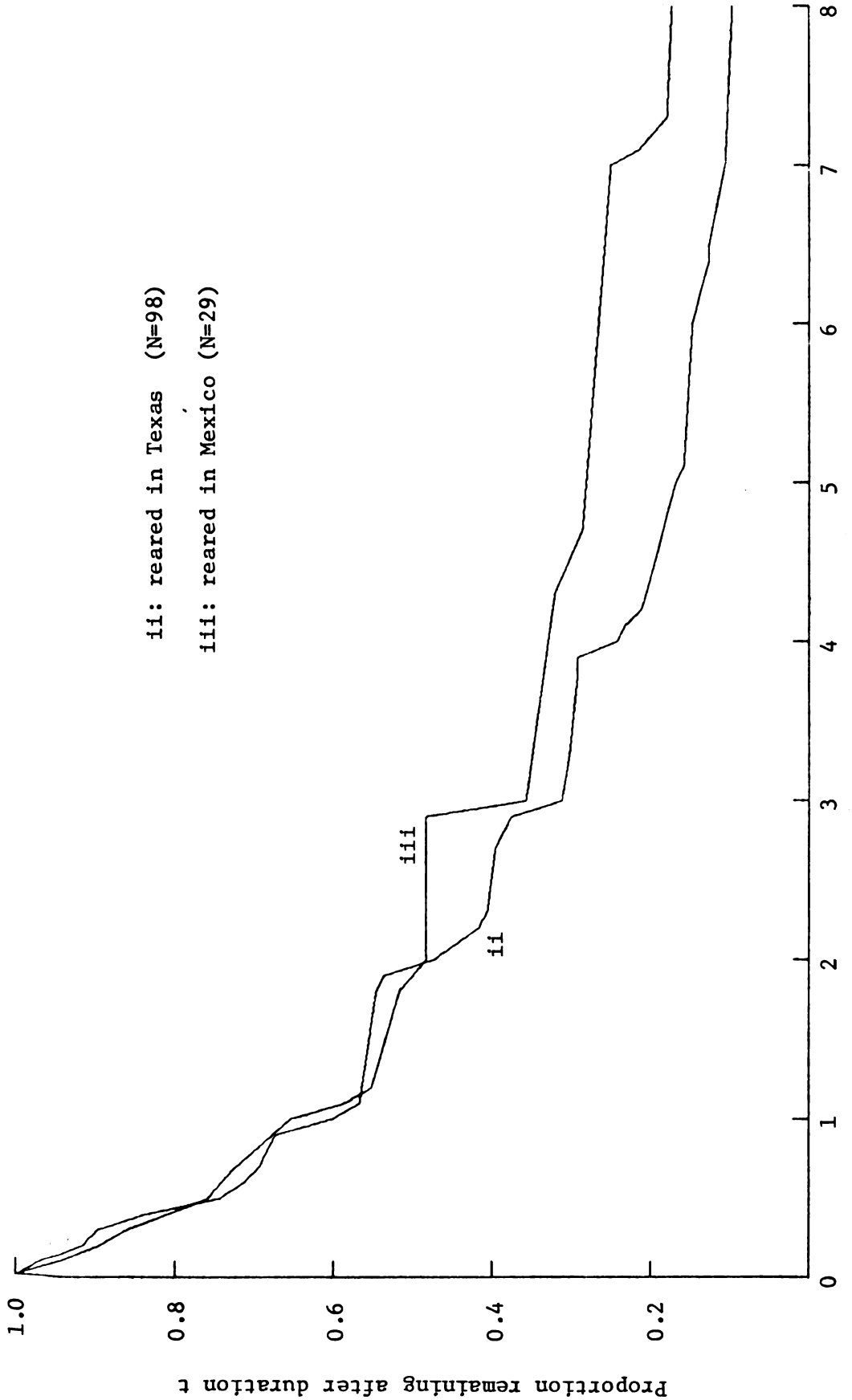

Figure 6.3 (c) Proportion of respondents with 0-3 years of completed schooling remaining in a job as a nonfarm laborer in Michigan or Texas (1935-1967) after duration t, by the location in which the respondent was reared.

Suppose that at time t_1 $s_j(t_1)$ respondents remain in job j, a of whom entered job j exactly t_1 years before the date of the interview. If the next observation is that b respondents left job j at time t_2, then

$$(6.2) \qquad G_j(t_2) = (s_j(t_1) - a - b)/(n_j(t_1) - a).$$

Thus if a or b is greater than zero, $G_j(t_1)$ is greater than $G_j(t_2)$:

$$(6.3) \qquad G_j(t_1) - G_j(t_2) = (a\,[1 - G_j(t_1)] + b)/(n_j(t_1) - a).$$

The magnitude of this difference increases as a and b increase and as $n_j(t_1)$ and $G_j(t_1)$ decrease. Since jobs begun in 1960-1967 tend to have comparatively large values of a for small values of duration t, we can expect the survival curves for this period to be seriously distorted in the downward direction even for short durations.

Because of this it is difficult to decide whether the difference between the survival curve for 1960-1967 and that for 1935-1959 resulted from this technical difficulty or from genuine increases in the instantaneous rate of leaving a job as a nonfarm laborer during 1960-1967. I have been unable to resolve this problem to my satisfaction.

(b) Nonmigratory farm laborers

The respondents' histories contain information on 289 jobs as a nonmigratory farm laborer, 190 of which were begun after 1934, in Michigan or Texas, and before the jobholder was fifty years of age. I examined plots of survival curves of nonmigratory farm laborers for each category of the variables listed in Table 6.2. Initially the respondent's educational level caused the most variation in the survival curves. I observed considerably less variation with previous experience in agriculture, number of previous sequences, and calendar year that the job began. The effect of the other variables was slight.

Table 6.2 Variables examined for nonmigratory farm laborers and for migratory farm laborers in Michigan with categories and number of observations.

	Nonmigratory Farm Laborers	Migratory Farm Laborers in Michigan
Geographical location		
Texas	95	0
Michigan	95	170
Educational level		
0-3 years of completed schooling	71	57
4-8	97	71
9-12	22	42
Location in which respondent was reared		
Mexico	31	15
Texas	145	123
Michigan	14	29
other	0	3
Migrant farm background		
no	68	52
yes	122	118
Calendar year that job began		
1935-1949	103	81
1950-1967	87	89
Respondent's age at entering the job		
16.0-24.9 years	114	97
25.0-49.9	76	73
Previous experience in same occupation		
no	103	80
yes	87	90
Previous experience in agriculture		
no	65	60
yes	125	110
Number of previous sequences		
0-2	106	75
3 or more	84	95

Next I held educational level constant and replotted the survival curves for previous experience in agriculture, number of previous sequences, calendar year that the job began, location of the job, and the location in which the respondent was reared. While some variation remained, none of these variables could account for the greater effect of educational level on survival curves of nonmigratory farm laborers.

(c) Migratory farm laborers

The respondents reported 513 instances of sequences with migratory farm laborer as the primary occupation, 256 of which were begun after 1934, in Texas or Michigan, and before the jobholder was fifty years of age. A preliminary examination of the data revealed that the geographical location of the job had a striking influence on the rate at which respondents left a job as a migratory farm laborer.

When survival curves for migratory farm laborers in Michigan were plotted using the categories of the variables listed in Table 6.2, only educational level had a noticeable effect. I did not try to analyze further the survival curves of migratory farm laborers in Michigan because of the initial lack of effect of other variables, the comparatively small number of observations on the three educational categories, and the extreme importance of accurate measurement of duration when, as in the case of migratory farm laborers in Michigan, the average duration in the job is short.

The initial influence of the variables listed in Table 6.3 on the survival curves of migratory farm laborers in Texas differed from the cases discussed thus far. The following variables had a conspicuous initial effect on the survival curves, in approximate order of decreasing effect: number of previous sequences (categorized 0-2 and 3

Table 6.3 Variables examined for migratory farm laborers in Texas with categories and number of observations.

Educational level	
0-3 years of completed schooling	67
4-8	97
9-12	22
Location in which respondent was reared	
Mexico	18
Texas	166
Michigan	2
other	0
Migrant farm background	
no	49
yes	137
Calendar year that job began	
1935-1944	71
1945-1954	75
1955-1959	19
1960-1967	21
Respondent's age at entering the job	
16.0-24.9 years	120
25.0-49.9	66
Previous experience in same occupation	
no	103
yes, immediately before the present job	23
yes, not immediately before the present job	60
Previous experience in agriculture	
no	89
yes, immediately before the present job	36
yes, not immediately before the present job	61
Number of previous sequences	
0	67
1	22
2	31
3	12
4 or more	54
Previous sequence nonagricultural	
no	103
yes	83

or more), calendar year that the job began (categorized 1935-1949 and 1950-1967), previous experience in the same occupation (categorized yes or no), previous experience in agriculture (categorized yes or no), migrant farm background, the respondent's educational level, and his age at entering the job.

I replotted the survival curves for calendar year that the job began using finer categories and found that the curves for categories within 1935-1959 closely resembled one another, but were much higher than the curve for 1960-1967. I tentatively hypothesized that the effect induced by the number of previous sequences could be explained by the calendar year that the job began since the two variables were highly correlated. But the survival curves for 1935-1959 varied greatly with the number of previous sequences.

Next I held the number of previous sequences constant and replotted the survival curves for previous experience in the same occupation, previous experience in agriculture, migrant farm background, educational level, and age at entering the job. Educational level, previous experience in agriculture, and age introduced some variation into the survival curves, but it was not sufficiently great to account for the effect of the number of previous sequences. The other two variables had little discernible effect on the survival curves.

Because the number of previous sequences was intended to test for undetected heterogeneity of the population, I was reluctant to conclude that the number of previous sequences was, in itself, the cause of the observed variation. Therefore my next step was to resolve the number of previous sequences into finer categories. Inspection of the survival curves for the categories 0, 1, 2, 3, and 4 or more previous

sequences proved useful. The survival curves declined fairly regularly as the number of previous sequences increased; furthermore, for the first two years the curve for 0 previous sequences, i.e., the first job, was markedly higher than the other curves. Consequently the categories 0, 1-3, and 4 or more previous sequences seemed more appropriate than my initial choice of 0-2 and 3 or more previous sequences.

Finding that the curve for the first job was decidedly higher than the curves for subsequent jobs led me to re-examine the effect of previous work experiences. As Table 6.3 shows, the number of observations for previous experience in the same occupation or in agriculture, immediately before the present job, is quite small. Because of this I had initially distinguished simply between having and not having previous experience. But at this point I replotted the survival curves for previous experience in the same occupation and in agriculture using the categories in Table 6.3.

When I superimposed the new plots for the number of previous sequences, previous experience in agriculture, and previous experience in the same occupation, the curve for 4 or more previous sequences was almost identical to the curves for previous experience, not immediately before the present job. In addition, the curves for 0 and 1-3 previous sequences closely approximated the curves for no previous experience and for previous experience, immediately before the present job. Therefore I hypothesized that variation in the survival curves induced by the number of previous sequences could be explained by previous experience in either migratory farm labor or agriculture.

I next plotted survival curves for previous experience in agriculture and previous experience in the same occupation for a fixed

number of previous sequences. All observations for 0 previous sequences, i.e., the first job, fell into the category of no previous experience. This curve declined very gradually, e.g., 87 percent remained in the job after 0.5 years. On the other hand, almost all observations for 4 or more previous sequences fell into the category of previous experience, but not immediately before the present job. This curve declined quite rapidly, e.g., about 49 percent remained in the job after 0.5 years.

The graph for 1-3 previous sequences showing survival curves for the three categories of previous experience in agriculture was the most interesting. The curve for experience in agriculture immediately before the present job declined slowly, e.g., 88 percent remained in the job after 0.5 years. For durations of several years this curve actually had greater proportions remaining in the job than any other curve, although it resembled fairly closely the curve for the first job. On the other hand, the curves for no previous experience in agriculture and previous experience in agriculture, but not immediately before the present job, were very similar and declined rapidly. In the early and most accurate portion of these curves they closely resembled the curve for 4 or more previous sequences.

In considering these patterns it occurred to me that the rate at which respondents left a job as a migratory farm laborer in Texas depended upon whether or not the previous sequence was nonagricultural. This hypothesis may be sensibly explained in terms of the framework employed in Chapter 3: both dissatisfaction with a job as a migratory farm laborer and the perceived ability to find a nonagricultural job should be greater for respondents whose previous job was

nonagricultural than for those whose previous job was agricultural or who had never worked before. I therefore constructed a new variable, previous sequence nonagricultural (categorized no and yes), listed at the bottom of Table 6.3, to summarize my generalization of the observed effect on survival curves of the two variables, number of previous sequences and previous experience in agriculture.

Finally I held constant the variable previous sequence nonagricultural and plotted survival curves by the respondent's educational level. On each graph the curves for 0-3 and 4-8 years of completed schooling were virtually identical. Although the curves for 9-12 years declined more rapidly than the curves for 0-8 years, the rate of leaving a job as a migratory farm laborer in Texas was enhanced much more by the previous sequence being nonagricultural than by a high educational level.

(d) Operatives

Because the respondents' histories contain information on 1252 jobs as an operative, more observations than for any other occupation, I anticipated no difficulty in identifying equivalent individuals in equivalent jobs for this occupation. This expectation was not fulfilled.

A preliminary examination of the data showed that industrial classification of a job as an operative had a marked effect on the rate at which respondents left the job. Two years after entering a job as an operative in Michigan, the percent remaining in the job was 32 for manufacturing of food and kindred products, 53 for fabricated metal manufacturing, and 63 for motor vehicle manufacturing.

Because the respondents' histories contained only 81 observations

on operatives in manufacturing of food and kindred products in Michigan, I did not analyze operatives in this industry further. However the number of observations on operatives in motor vehicle and fabricated metal manufacturing in Michigan appeared adequate for further investigation: 332 and 297, respectively. I restricted the analysis to jobs occurring in Michigan because 97 percent of respondents' jobs as an operative in motor vehicle manufacturing, and 89 percent of those in fabricated metal manufacturing, occurred in this location.

I then plotted and examined survival curves of operatives in these two industries in Michigan for the categories of the variables listed in Table 6.4. In both industries the survival curves varied most with the location in which the respondent was reared and with the calendar year that the job began. The two industries differed with regard to the effect of other variables. For operatives in fabricated metal manufacturing, the respondent's educational level introduced almost as much variation as the location in which he was reared, while previous experience in agriculture and in fabricated metal manufacturing had a noticeable but considerably smaller effect. For operatives in motor vehicle manufacturing, the respondent's age at entering the job, migrant farm background, and previous experience in motor vehicle manufacturing influenced the survival curves somewhat, although much less than either the location in which the respondent was reared or the calendar year that the job began. The respondent's educational level had almost no effect on the rate of leaving a job as an operative in motor vehicle manufacturing.

In order to clarify the effect of calendar year on the survival curves, I replotted the curves for each industry using finer

Table 6.4 Variables examined for operatives in Michigan with categories and number of observations, by industry.

Industry		
fabricated metal manufacturing	297	0
motor vehicle manufacturing	0	332
Educational level		
0-3 years of completed schooling	92	61
4-8	119	132
9-12	86	139
Location in which respondent was reared		
Mexico	40	40
Texas	188	204
Michigan	63	86
other	6	2
Calendar year that job began		
1935-1944	50	25
1945-1954	125	125
1955-1967	122	182
Respondent's age at entering the job		
16.0-24.9 years	130	143
25.0-49.9	167	189
Previous experience in same occupation		
no	102	117
yes, immediately before the present job	108	119
yes, not immediately before the present job	87	96
Previous experience in same industry		
no	169	210
yes, immediately before the present job	62	55
yes, not immediately before the present job	66	67
Previous experience in agriculture		
no	106	142
yes, immediately before the present job	59	42
yes, not immediately before the present job	132	148
Number of previous sequences		
0-2	58	82
3 or more	239	250

categories: 1935-1944, 1945-1949, 1950-1954, 1955-1959, and 1960-1967. For operatives in both industries the effect of calendar year was not limited to 1960-1967, as in other occupations, and could not be attributed to the method of calculation. For the first year and a half in the job operatives in both industries left at a much more rapid rate during 1935-1944 than the post-War years. The profound impact of World War II on the industrial sector of Michigan's economy may account for this difference. In any case the number of observations on operatives who entered the job during 1935-1944 was too small to support further investigation of survival curves for this period.

Comparison of the survival curves for 1945-1954, 1955-1959, 1960-1962, and 1963-1967 suggested that differences between the curves could reasonably be ascribed to the method of calculation (cf. Section 6.1a). Thus the curve for 1945-1954 agreed closely with the curve for 1955-1959 for approximately the first thirteen years, with the curve for 1960-1962 for the first five years, and with the curve for 1963-1967 for the first two years. So I concluded that operatives entering jobs in both industries during 1945-1967 began work at equivalent points in calendar time insofar as their survival curves were concerned. There remained for further investigation with other variables an apparently adequate number of observations on operatives who entered both industries in Michigan during 1945-1967: 247 in fabricated metal manufacturing and 307 in motor vehicle manufacturing.

With the effect of calendar year controlled by eliminating the data for 1935-1944, the location in which the respondent was reared remained as the sole variable with a substantial initial influence on the survival curves of operatives in the two industries. Because the

respondent's educational level had accounted for the effect of the location in which he was reared on the survival curves of nonfarm laborers and nonmigratory farm laborers, I tentatively hypothesized that this would also be the case for operatives. Consequently I replotted the survival curves of operatives in both industries by educational level (categorized 0-3, 4-8, 9-10, and 11-12 years of completed schooling) for a fixed location in which the respondent was reared.

Although individual survival curves were based on a small number of observations, the patterns for operatives in fabricated metal manufacturing were remarkably clear-cut. First, for a fixed location in which the respondent was reared, the curves for 0-3 and 4-8 years were almost identical, as were the curves for 9-10 and 11-12 years. Therefore I replotted the survival curves by educational level (categorized 0-8 and 9-12 years of completed schooling) and by the location in which the respondent was reared. For respondents reared in Texas and in Michigan the curve for 0-8 years was extremely similar to that for 9-12 years for durations less than one year; however, for both groups the curve for 0-8 years was sharply higher than the curve for 9-12 years after two or more years duration. Apparently the location in which the respondent was reared determined the rate of leaving the job during the first year or two, while the respondent's educational level determined the eventual proportion remaining in the job after a long period of time. Such a conclusion is, of course, quite tentative because of the few observations for most of the survival curves.

On the other hand, for operatives in motor vehicle manufacturing the survival curves by educational level (also categorized 0-3, 4-8, 9-10, and 11-12 years of completed schooling) for a fixed location in

which the respondent was reared showed no clear pattern, except that for respondents reared in Michigan and in Texas, the curve for 11-12 years declined more slowly than the curves for fewer years of schooling. Aside from my observation that nonfarm laborers with 0 years of completed schooling left more rapidly than those with 1-3 years, this was the only observation of a reversal of the finding that the rate of leaving the job increased with the respondent's educational level.

The unusualness of this observation led me to replot the survival curves of operatives in motor vehicle manufacturing using finer categories of educational level, namely, 0-7, 8, 9, 10, 11, and 12 years of completed schooling. The curves for 0-7, 8, 11, and 12 years clustered together considerably above the similar curves for 9 and 10 years, suggesting 0-8, 9-10, and 11-12 years as categories.

I replotted the survival curves of operatives in motor vehicle manufacturing by the location in which the respondent was reared for a fixed educational level (categorized 0-8, 9-10, and 11-12 years of completed schooling). When I superimposed the graphs for 0-8 and 9-10 years, I observed a pattern somewhat similar to that for operatives in fabricated metal manufacturing: the location in which the respondent was reared had a marked effect on the rate of leaving for durations less than two years, while educational level had the predominant effect for longer durations. Because some curves were based on very few observations, the effect of educational level on the tail of the survival curves may have resulted from random variation, and, in any case, was much less than I observed for operatives in fabricated metal manufacturing.

The graph for 11-12 years of completed schooling showed that

respondents reared in Michigan left the job somewhat faster than those reared in Texas. However, even for short durations respondents reared in Michigan and in Texas with 11-12 years of completed schooling left more slowly than those reared in the same location but with a lower educational level. Thus, while both the location in which the respondent was reared and his educational level apparently influenced the rate at which respondents left a job as an operative in motor vehicle manufacturing, the nature of their influence cannot be summarized in a simple fashion as in the case of operatives in fabricated metal manufacturing.

The number of observations on respondents in a job as an operative in either fabricated metal or motor vehicle manufacturing who had a fixed educational level and were reared in a fixed location was small except for those reared in Texas with 0-8 years of completed schooling. Consequently I investigated the effect of the remaining variables only on survival curves of respondents with these attributes, i.e., 122 operatives in fabricated metal manufacturing and 137 operatives in motor vehicle manufacturing.

For each group I plotted survival curves for the following variables: the respondent's age at entering the job, migrant farm background, previous experience as an operative, previous experience in fabricated metal manufacturing, previous experience in motor vehicle manufacturing, previous experience in agriculture, the number of previous sequences, previous occupation, and previous industry. Because of the small number of observations for individual survival curves, these plots could not conclusively establish which variables significantly affected the rate at which operatives left a job in either

industry. However, considerable variation, primarily in the tail of the curves, occurred only on graphs of variables pertaining to previous work experience. Obviously the influence of previous experiences on the rate of leaving jobs merits further study.

6.2 The findings by issue

(a) Identification of equivalent social positions

I investigated the effect on survival curves, and concomitantly on the rate of leaving a job, of three job attributes: occupational classification, industrial classification, and geographical location. As expected, the rate at which respondents left a job varied noticeably with its attributes. For respondents with a given educational level (in most jobs the most influential attribute of those examined), the rate of leaving the job decreased in approximately the following order: migratory farm laborers in Michigan, nonfarm laborers in Michigan or Texas, nonmigratory farm laborers in Michigan or Texas, operatives in fabricated metal manufacturing in Michigan, operatives in motor vehicle manufacturing in Michigan. A job as a migratory farm laborer in Texas is not easily compared with the other jobs because previous sequence nonagricultural, rather than educational level, most affected the survival curves for this job. However, the range of the curves for migratory farm laborers in Texas resembled the range of the curves for nonfarm laborers.

As expected, the rate of leaving a job appeared to be negatively correlated with the level of social rewards (money, social prestige, etc.) with which the job is associated, as inferred primarily by the occupational classification of the job, and also by industrial classification in the case of operatives. This finding, coupled with the

observation that the rate of leaving the job usually rose with educational level, suggests that in most cases jobs were terminated by the jobholder and supports my argument in Chapter 3 that job dissatisfaction is a major factor determining the rate at which an individual terminates his job.

Although location had no discernible impact on the survival curves of nonfarm laborers and nonmigratory farm laborers, its effect on the curves of migratory farm laborers was considerable. A change in location from Michigan to Texas significantly lowered the rate of leaving this occupation and also apparently altered the attributes of respondents most affecting the process of leaving this job. Migratory farm labor, like unemployment, seems to function as a labor pool, i.e., as a state to which most individuals have little commitment and leave whenever they perceive the opportunity. Nonagricultural jobs are proportionately more abundant in Michigan than in Texas, and respondents probably reacted to this difference in leaving jobs as migratory farm laborers more rapidly in the former location. Thus this finding offers evidence that the rate of leaving jobs depends substantially on ability to find other employment, and not solely on the individual's job satisfaction.

Note that although all jobs investigated are usually assigned to the bottom quartile of occupational status scores, the rate at which respondents left these jobs varied widely: as much as ten-fold for a relatively homogeneous subpopulation. These observations suggest that in modeling social mobility, jobs in different occupations and industries should not be treated as equivalent social positions solely because their status scores (e.g., cf. Reiss, 1961) are similar. The

findings also indicate that social differences between migratory and nonmigratory farm labor are sufficiently great to warrant treatment as separate occupational categories.

(b) Identification of equivalent individuals

I investigated the effect on survival curves of three fixed attributes of respondents: educational level, the location reared, and migrant farm background. As anticipated, in most cases educational level was significantly and positively correlated with the rate of leaving the job, although for operatives its effect was subordinate to the location in which the respondent was reared. Since it is highly improbable that employer-initiated and unintentional job terminations rise with educational level, the prevalence and strength of this pattern indicates that most jobs were terminated by the jobholder.

In two cases I found an inverse relationship between educational level and the rate of leaving the job: nonfarm laborers with 0 years of completed schooling left more rapidly than those with 1-3 years, and operatives in motor vehicle manufacturing in Michigan with 11-12 years of completed schooling left less rapidly than those with less schooling. As the findings were based on rather small numbers of observations (ranging from 24 to 52), random variation may account for these reversals.

The initial, noted influence of the location in which the respondent was reared on the survival curves of nonfarm laborers and of nonmigratory farm laborers was adequately explained by the highly related variation in educational level. However, the effect of the location in which the respondent was reared on the rate at which operatives in both fabricated metal and motor vehicle manufacturing in

Michigan left could not be attributed to any other variable examined. That this variable affected the rate of leaving the job was not surprising; the magnitude of its effect relative to that of educational level was unanticipated. Since it seems unlikely that either employer-initiated job terminations or opportunities for employment significantly depend on the location in which jobholders were reared, the influence of the location in which the respondent was reared on the survival curves of operatives suggests the importance of the individual's subjective assessment of his job and of his opportunities for more satisfactory employment. That operatives reared in Michigan left more rapidly than those reared in Texas and that the latter left more rapidly than those reared in Mexico implies that, as postulated, those reared in locations oriented more towards agriculture and less towards industry either evaluate jobs in industry more favorably or have lower expectations of their ability to improve upon such a job, or both.

While migrant farm background introduced some variation into the initial survival curves for migratory farm laborers in Texas and for operatives in motor vehicle manufacturing in Michigan, other variables adequately accounted for this variation. This negative finding deserves attention because it indicates that a migrant farm background per se does not greatly affect either the individual's evaluation of his job or of his opportunities for better employment.

(c) The correspondence between the theoretical construct time t and observable measures of time

I directly investigated the effect of two measures of time on survival curves, the calendar year that the job began and the

individual's age at entering the job. Evidence on the influence of the third measure of time, the duration in the job, is indirect. If the rate of leaving does not depend on duration, then Probability Law I should describe the process of equivalent individuals leaving equivalent jobs. Thus in testing the validity of Probability Law I, one weighs the influence of duration on the rate of leaving the job. Consequently the report on the effect of duration is delayed until the discussion of findings pertaining to Probability Law I in Section 7.

Initially I restricted my analysis to jobs entered after 1934 in order to avoid major disturbances in job mobility resulting from the Depression of the early 1930's; the upper limit was fixed by the date of the respondent's interview, which took place during the winter of 1967-1968. Thus I examined the stability of the rate of leaving jobs over a period of thirty-three calendar years.

For each occupation examined, respondents entering the job during 1945-1959 appeared to begin work at equivalent points in calendar time insofar as their survival curves in these occupations were concerned. For nonfarm laborers, nonmigratory farm laborers, and migratory farm laborers the years 1935-1944 were indistinguishable from 1945-1959. However, the initial rate of leaving the job for operatives in both fabricated metal and motor vehicle manufacturing was considerably greater during 1935-1944 than during the post-War years. I did not explore this finding further because of insufficient data on operatives entering the job in 1935-1944, but the impact of World War II on Michigan's factories is a possible source of this difference.

For migratory farm laborers, nonmigratory farm laborers, and operatives the years 1960-1967 seemed equivalent to 1945-1959. But

nonfarm laborers appeared to leave the job much more rapidly during 1960-1967 than in previous years. As I reported in the findings for this occupation, I lacked the information needed to decide whether survival curves for 1960-1967 declined more rapidly than for previous years because of genuine increases in the rate of leaving the job or because of distortions introduced by the method of calculation.

Because the number of observations on respondents entering the job after age fifty was small, I limited the investigation of the influence of age on survival curves to ages less than fifty years. The lower age limit was fixed by the interview schedule at sixteen years. I divided age into two categories: 16.0-24.9 and 25.0-49.9 years. There were two reasons for this choice of categories. First, this division gave approximately equal numbers of observations for the two categories, and secondly, after nearly ten years in the labor force, most individuals should no longer be searching for a permanent job (cf. Miller and Form, 1951).

For each occupation examined, when the most significant variables affecting the survival curves were controlled, the impact of the respondent's age at entering the job was weak to nonexistent. This may seem surprising as it has been widely asserted that job mobility decreases as age increases (e.g., cf. Miller and Form, 1951). However, this assertion does not necessarily imply that the rate of leaving the job decreases with age at entering the job. The probability of changing jobs may decrease as age increases because: (1) the rate of leaving jobs decreases with increases in duration and an increase in age always accompanies an increase in duration; (2) as their age increases, individuals changing jobs are more likely to enter jobs in occupations

with an inherently lower rate of leaving. As an example of the latter, the respondents may tend to shift from jobs as a migratory farm laborer to jobs as an operative. If the first reason is the sole cause of decreases in job mobility with increases in age, then the effect of age is spurious and its importance as an independent variable should be downgraded. Further research is needed to settle this issue.

(d) The validity of the Markov assumption

My primary aim was to discover whether or not previous work experiences influenced the rate at which individuals left jobs. To achieve this I compared survival curves of respondents varying with regard to previous experience in the occupation or industry of the job being examined, generally using the categories no experience, experience immediately before the present job, and experience not immediately before the present job.

In most cases these variables only slightly affected the survival curves of respondents in a given job. Migratory farm laborers in Texas were a notable exception. I concluded that my findings concerning this job were best summarized in terms of a newly constructed variable, previous sequence nonagricultural (categorized no and yes). I found no variable that introduced greater changes into the rate of respondent's leaving a job as a migratory farm laborer in Texas than did this new variable, with those in the yes category leaving much faster than those in the no category.

This suggests that those in the former category were more likely than those in the latter to be dissatisfied with a job as a migratory farm laborer and to perceive that they could obtain a better and presumably nonagricultural job. This seems plausible. It also implies

that my original analysis of the effect of previous work experiences on the rate of leaving jobs (cf. Section 3.5) was formulated incorrectly. Whereas I focused on the similarity of previous experiences to the present job, I now think that it would have been wiser to have examined the effect on survival curves of either the occupation and industry of the previous job or of differences in the level of satisfaction offered by the present and previous jobs. With regard to the latter, one reasonable hypothesis is the following: the rate of leaving the job increases when the present job is less satisfactory than the previous one and decreases when it is more satisfactory than the previous one. Either wage level or occupational status scores (cf. Reiss, 1961) could be used to infer differences in the level of satisfaction whenever the respondent's own evaluation of these jobs is unavailable. Wilensky's (1959) finding that work-life skidders were more likely than non-work-life skidders to indicate low commitment to their factory and low interest in workplace mobility offers indirect support for this hypothesis.

While all issues examined in this research need further study in order to give greater assurance and generality to my conclusions, the effect of previous work experiences on the rate of leaving jobs deserves special attention. Such research would not only guide the formulation of future stochastic models of social mobility but also provide practical information concerning the relative influence of job experience and educational level on the ability of members of a low status subpopulation to improve their social position during their own lifetime.

(e) The validity of Approaches A, B, and C

In general, information to distinguish among Approaches A, B, and C must pertain to activity within states of the system, an unknown in the employment-residence histories used as data in the present study. However I did propose one test that can be used with work history data to detect population heterogeneity that causes a consistent effect on the rate of leaving jobs, and hence to assess the validity of Approach B, the assumption of population heterogeneity. This test consists of comparing the survival curves of individuals who vary in the number of jobs held prior to the one being examined. If a fixed attribute of individuals has a consistent effect on the rate of leaving jobs, then individuals with values of this attribute causing a rapid rate of leaving should on the average occupy more jobs per unit of time, and therefore have a greater number of previous sequences.

As this test strictly requires that individuals being compared have the same occupational background, I doubted its usefulness. And, indeed, while the number of previous sequences caused some variation, usually minor, in the initial plots of survival curves, with one exception I easily found other variables that adequately accounted for this variation. The exception occurred in my investigation of migratory farm laborers in Texas. The number of previous sequences induced large variation into survival curves for this job and its effect could not be attributed to any of the original variables being examined.

A new variable, previous sequence nonagricultural, seemed to summarize satisfactorily the variation in survival curves of migratory farm laborers in Texas which I observed with different variables (cf. Section 6.1c). If I had omitted the number of previous sequences as

a variable, I doubt that I would have resolved the problems encountered with this job or formulated my final generalization concerning it. In addition, the lack of influence that this variable had on survival curves of other jobs offers some evidence that relatively homogeneous subpopulations were eventually identified.

CHAPTER 7

The Process of Individuals Leaving a Social Position: Evaluation and Interpretation of Probability Laws

In order to evaluate a probability law intended to describe the process of equivalent individuals leaving equivalent jobs one must first identify equivalent individuals in equivalent jobs. This was the object of the research reported in Chapter 6. Reasonably equivalent individuals in equivalent jobs were apparently identified successfully for three job categories: nonmigratory farm laborers, migratory farm laborers in Texas, and operatives in fabricated metal manufacturing in Michigan (1945-1967).

Results with three other job categories were less satisfactory for the following reasons: (1) Nonfarm laborers with a given educational level seemed to be relatively equivalent individuals in equivalent jobs; however, I was unable to determine whether an apparent increase in the rate of leaving during 1960-1967 was genuine or a methodological artifact (cf. Section 6.1a). (2) Educational level appeared to have the most effect on the rate of leaving a job as a migratory farm laborer in Michigan, but I did not thoroughly investigate this job category because of the comparatively few observations and the extreme rapidity with which respondents left the job. (3) The location in which a respondent was reared noticeably influenced the rate of leaving a job as an operative in motor vehicle manufacturing in Michigan (1945-1967). The less prominent effect of educational level was puzzling

because respondents reared in Texas and in Michigan with 11-12 years of completed schooling left the job somewhat less rapidly than their counterparts with a lower educational level. Although the proportion of respondents reared in Texas and in Michigan remaining in the job after more than two years was smaller for those with 0-8 than 9-10 years of completed schooling, the differences seemed small enough that those with 0-10 years of completed schooling could be treated as equivalent individuals.

In spite of these problems with the latter three job categories, I have included them in the parameter estimation phase of the research. The six job categories produce a total of twenty-one sets of data on what I have treated as equivalent individuals in equivalent jobs. A description of each data set with its symbolic designation is given in Table 7.1. Even though some data sets may not correctly identify equivalent individuals in equivalent jobs, the results presented in the rest of this chapter remain of interest as illustrations of the ability of the probability laws examined to describe the process of individuals leaving jobs.

Before evaluating the ability of a probability law to predict the rate at which equivalent individuals leave equivalent jobs, one must also select a method of estimating parameters. In this study I estimated parameters by two commonly used means: the method of maximum likelihood and the method of least squares. The method of maximum likelihood weights equally each observation on an individual in a job, whereas the method of least squares, as utilized in this study, weights equally each point on an observed curve of the proportion remaining in job j after duration t, $G_j(t)$, versus duration t.

Table 7.1 Description of data sets of apparently equivalent individuals in equivalent jobs with symbolic designation.

Symbol	Description of data set
A	Migratory farm laborers in Michigan (1935-1967)
a	9-12 years of completed schooling
b	4-8 years of completed schooling
c	0-3 years of completed schooling
B	Migratory farm laborers in Texas (1935-1967)
a	previous sequence nonagricultural
b	previous sequence not nonagricultural
C	Nonfarm laborers in Michigan and Texas (1935-1967)
a	9-12 years of completed schooling
b	4-8 years of completed schooling
c	0-3 years of completed schooling
D	Nonmigratory farm laborers in Michigan and Texas (1935-1967)
a	9-12 years of completed schooling
b	4-8 years of completed schooling
c	0-3 years of completed schooling
E	Operatives in fabricated metal mfg. in Michigan (1935-1967)
a	reared in Michigan, 9-12 years of completed schooling
b	reared in Michigan, 0-8 years of completed schooling
c	reared in Texas, 9-12 years of completed schooling
d	reared in Texas, 0-8 years of completed schooling
e	reared in Mexico, 0-12 years of completed schooling
F	Operatives in motor vehicle mfg. in Michigan (1935-1967)
a	reared in Michigan, 0-10 years of completed schooling
b	reared in Texas, 0-10 years of completed schooling
c	reared in Michigan, 11-12 years of completed schooling
d	reared in Texas, 11-12 years of completed schooling
e	reared in Mexico, 0-12 years of completed schooling

Consequently a theoretical curve calculated from least squares parameter estimates should always fit the observed curve of $G_j(t)$ versus duration t as well as, and usually better than, the comparable curve calculated from maximum likelihood parameter estimates. Nevertheless, the method of maximum likelihood should give better estimates of the true parameter values because it weights observations in the raw data more reasonably than the method of least squares. For this reason my evaluation of different probability laws in this chapter is based entirely on parameter estimates obtained by the method of maximum likelihood. For purposes of comparison I have reported the parameter estimates obtained by the method of least squares in Appendix C.

7.1 Findings concerning Probability Law I

Table 7.2 reports values of the maximum likelihood estimate κ^* and other statistics pertaining to Probability Law I for the twenty-one data sets examined. Figures 7.1 through 7.6 show plots of the observed curves of $G_j(t)$ versus duration t with the corresponding curves predicted by Probability Law I with the maximum likelihood estimate κ^* for the six job categories studied. Appendix D contains the tables for the twenty-one data sets from which the observed curves of $G_j(t)$ versus duration t and the corresponding curves predicted by various probability laws were constructed.

Visual comparison of the observed curves of $G_j(t)$ versus duration t and the corresponding curves predicted by Probability Law I indicates that Probability Law I should be rejected for fifteen data sets (Aa, Ab, Ac, Ba, Ca, Cb, Cc, Da, Ea, Eb, Ec, Ed, Fa, Fb, Fc). For these data sets the curve predicted by Probability Law I declines too slowly for small values of duration t and in some cases too rapidly for large

Table 7.2 Statistics pertaining to maximum likelihood parameter estimates for Probability Law I[1].

Data set	$n_j(0)$	κ^*	S_I^*	$-\ln L_I^*$	χ^2	df	Prob[χ^2/df]
Aa	42	1.787	.222	17.612	28.3	3	< .00001
Ab	71	.967	.369	73.360	56.3	6	< .00001
Ac	57	.596	.749	84.945	40.3	4	< .00001
Ba	83	.527	.574	136.116	62.8	7	< .00001
Bb	103	.239	.093	250.623	20.4	9	.016
Ca	130	.694	.112	165.163	26.2	9	.002
Cb	209	.395	.396	374.343	69.1	9	< .00001
Cc	129	.269	.275	277.647	35.4	9	.00005
Da	22	.437	.121	36.571	0.2	1	.65
Db	97	.299	.098	191.925	23.1	7	.002
Dc	71	.203	.060	171.337	6.9	5	.23
Ea	38	.563	.352	45.654	0.3	1	.58
Eb	18	.134	.463	33.124	-	-	-
Ec	39	.201	.407	67.725	5.5	1	.02
Ed	122	.088	1.391	246.710	20.4	6	.002
Ee	24	.095	.120	47.005	-	-	-
Fa	41	.176	.944	71.217	1.4	1	.24
Fb	170	.083	1.478	300.325	12.4	7	.09
Fc	38	.090	.643	54.457	-	-	-
Fd	24	.082	.203	38.458	-	-	-
Fe	32	.044	.480	57.682	-	-	-

[1]Values of χ^2 were calculated as described by Epstein (1960a: 85-86; 1960b).

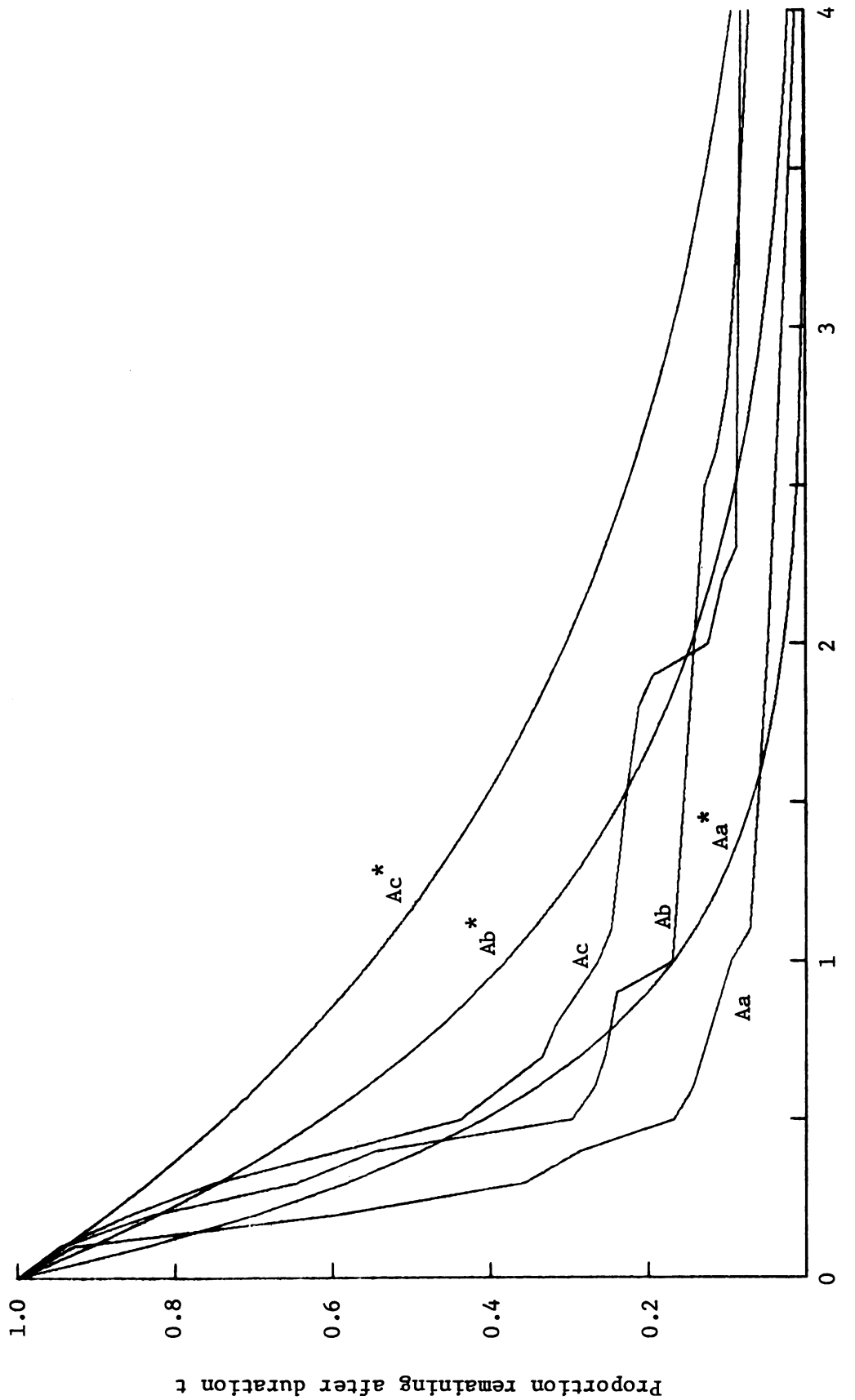

Figure 7.1 Proportion remaining in the job after duration t for data sets Aa, Ab, and Ac. Values observed and predicted by Probability Law I.

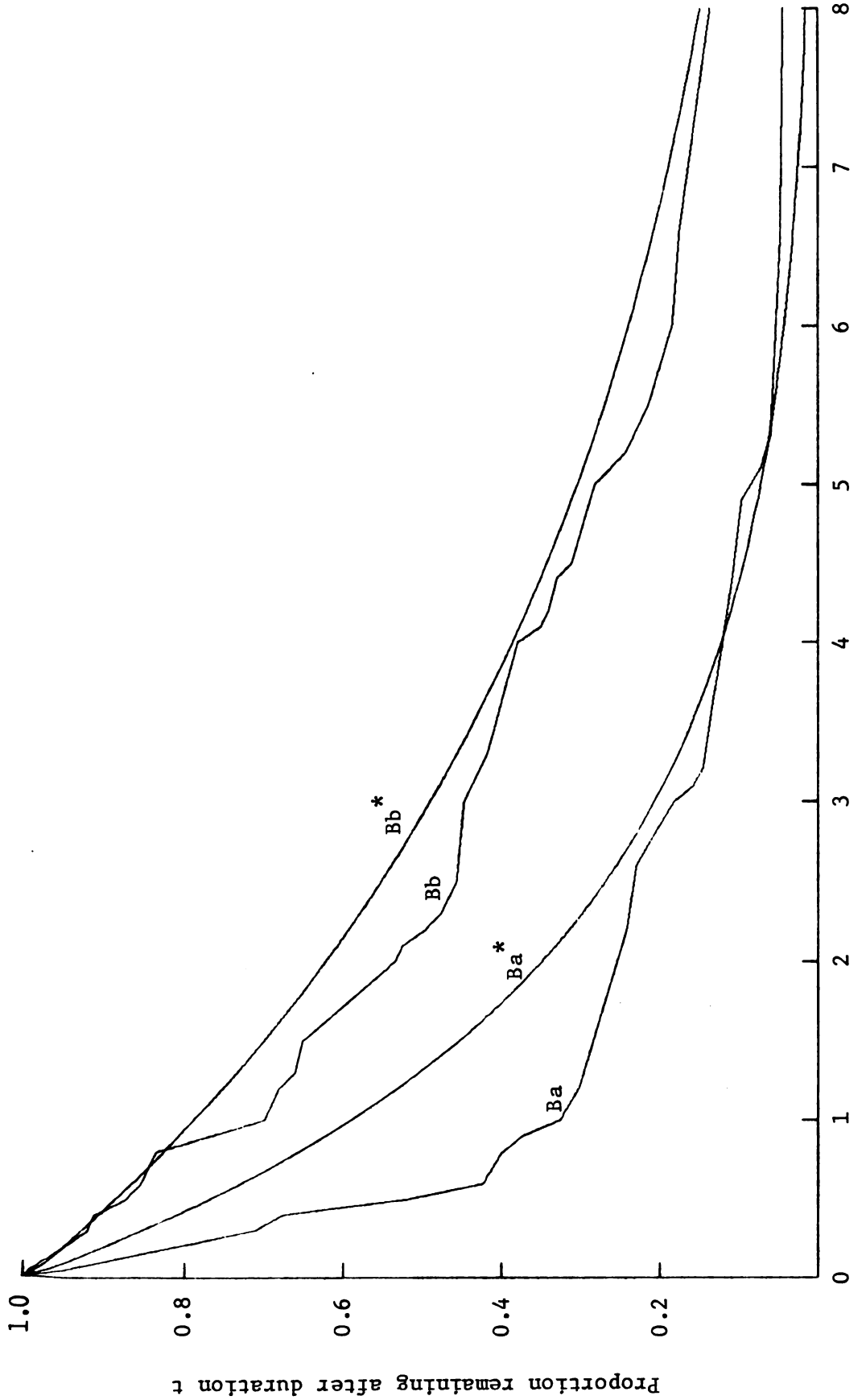

Figure 7.2 Proportion remaining in the job after duration t for data sets Ba and Bb.
Values observed and predicted by Probability Law I.

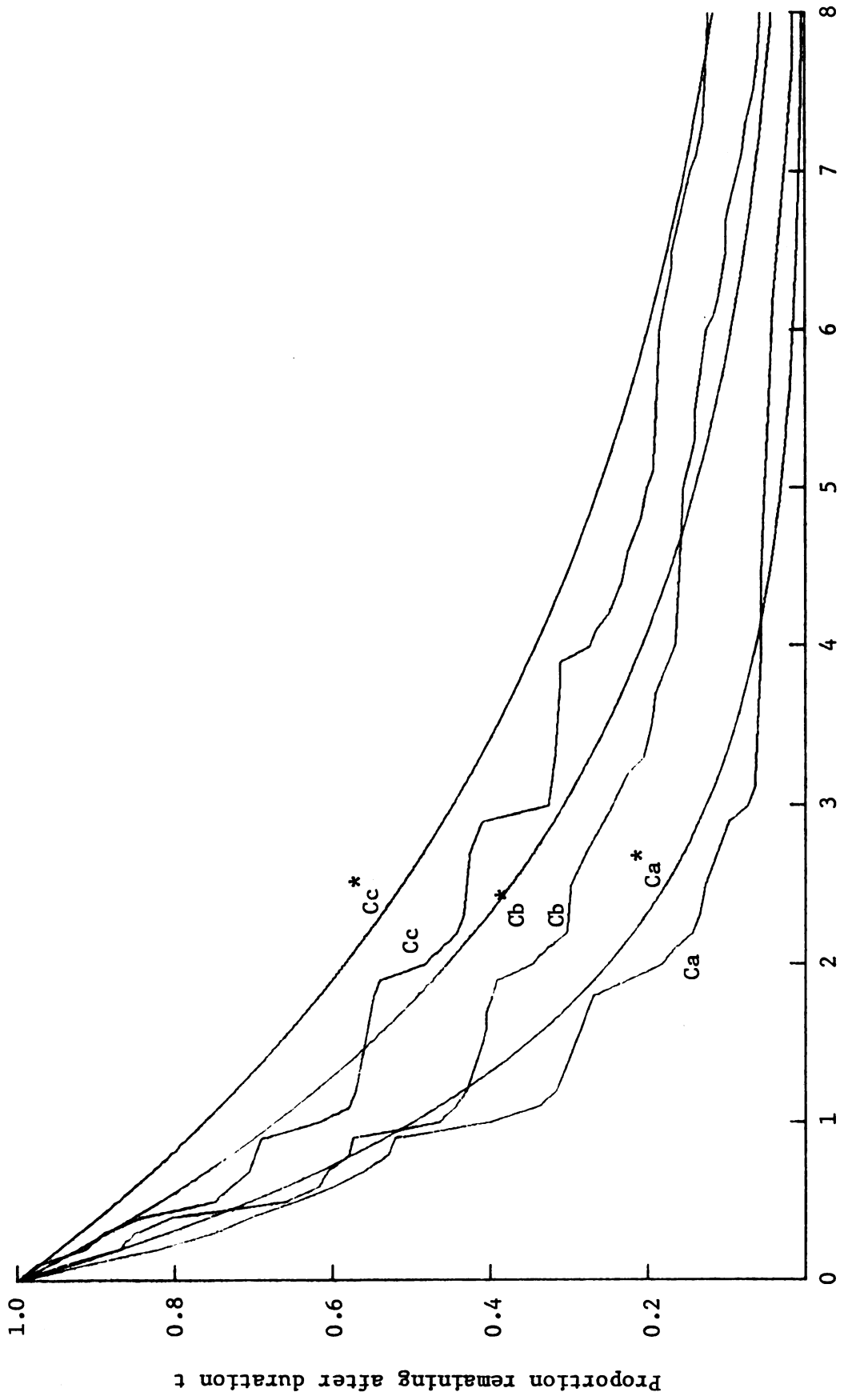

Figure 7.3 Proportion remaining in the job after duration t for data sets Ca, Cb, and Cc. Values observed and predicted by Probability Law I.

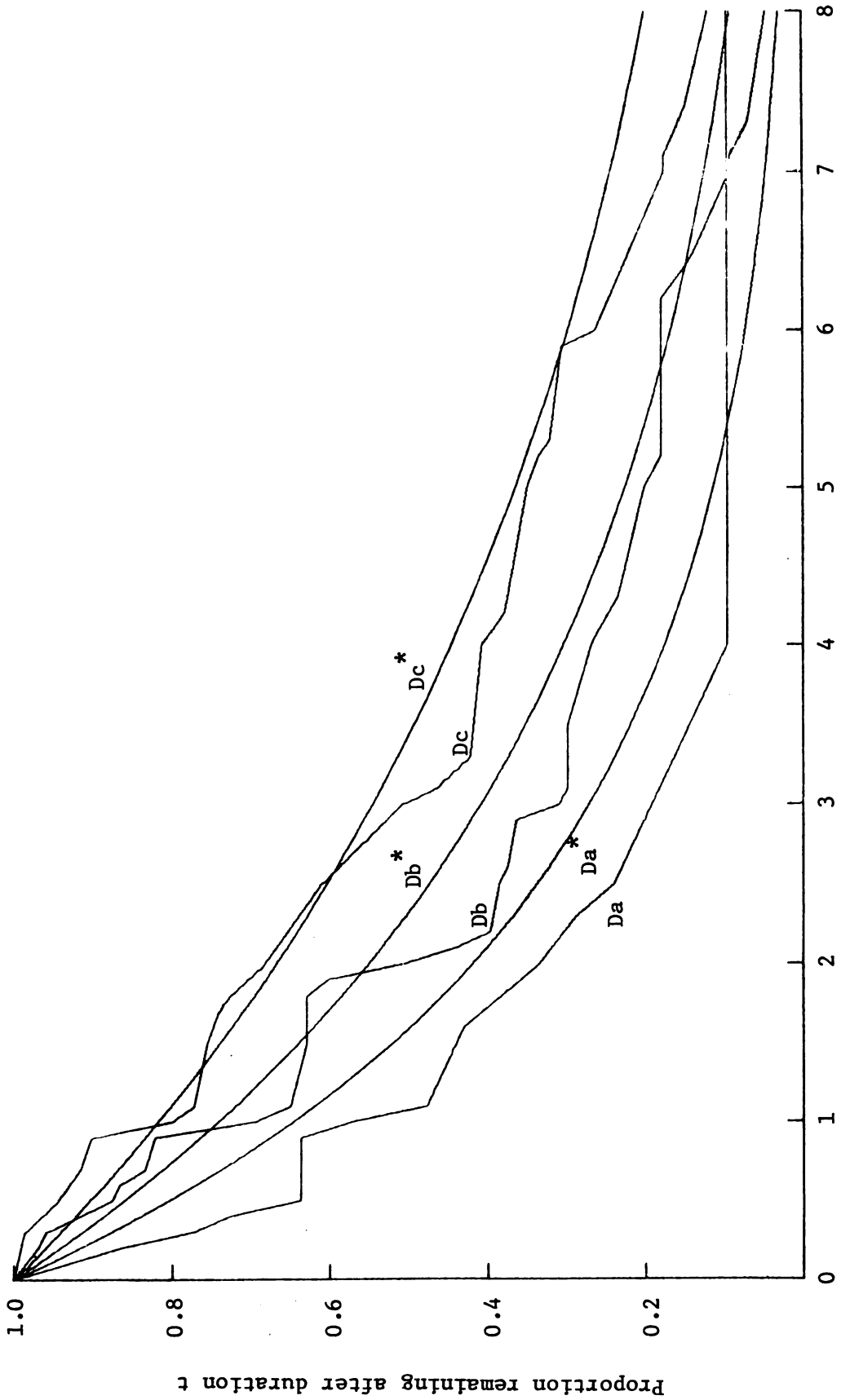

Figure 7.4 Proportion remaining in the job after duration t for data sets Da, Db, and Dc. Values observed and predicted by Probability Law I.

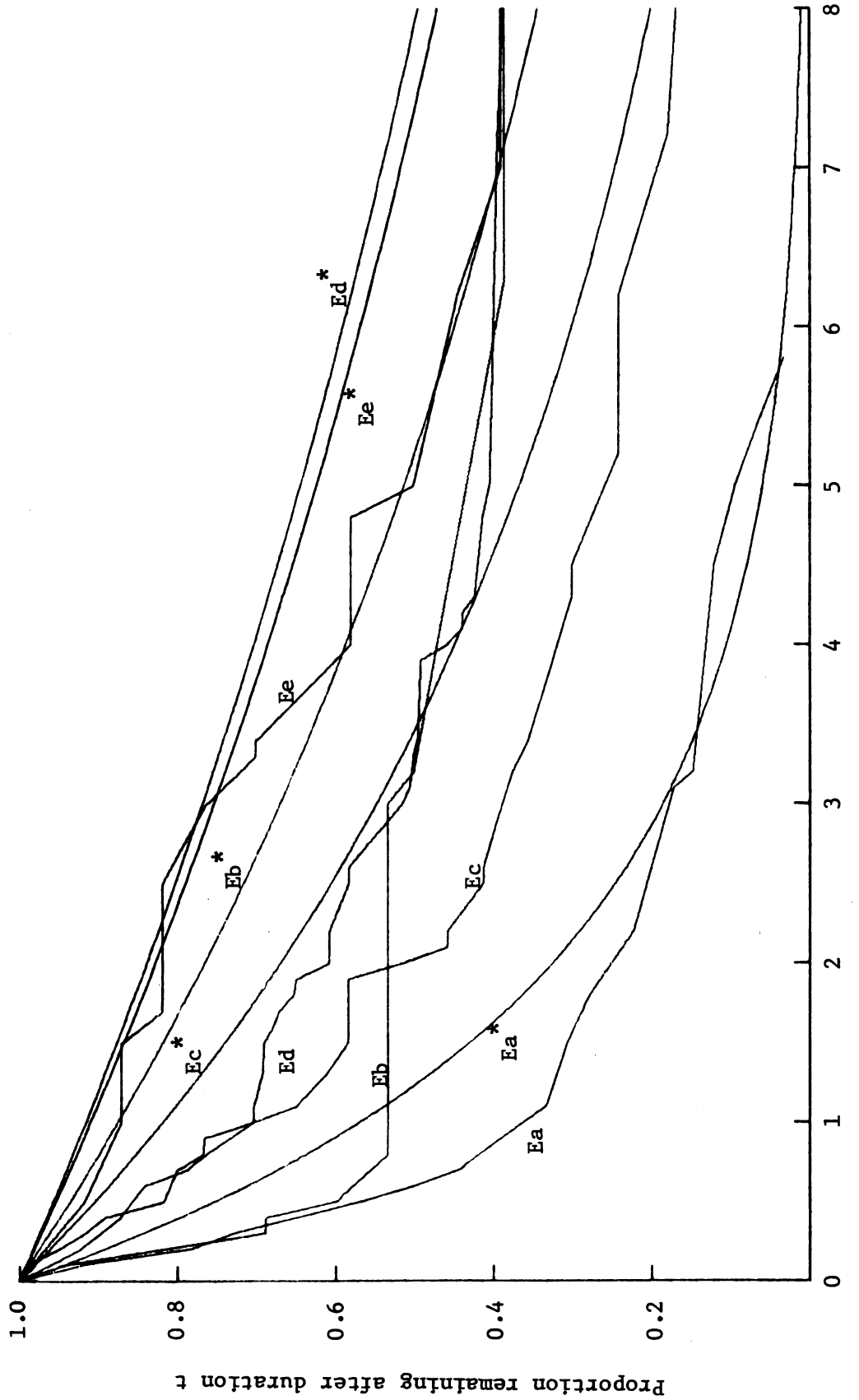

Figure 7.5 Proportion remaining in the job after duration t for data sets Ea, Eb, Ec, Ed, and Ee. Values observed and predicted by Probability Law I.

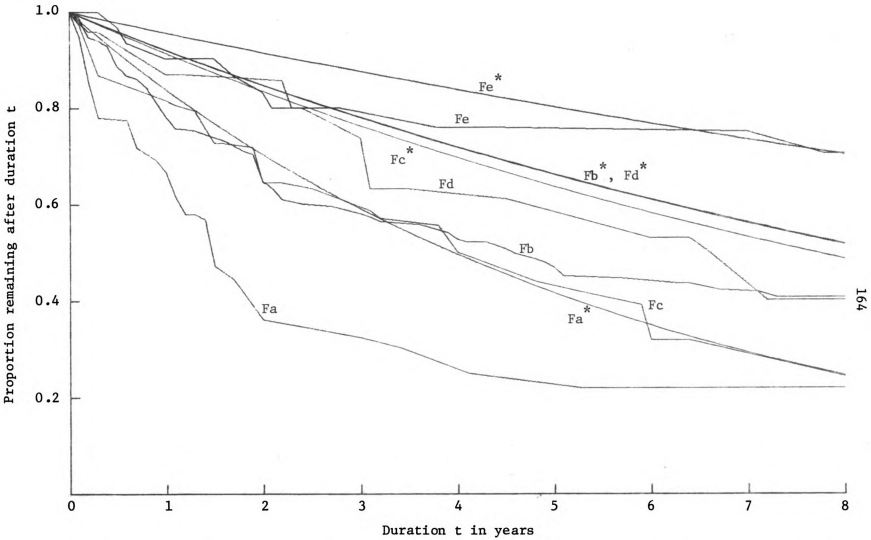

Figure 7.6 Proportion remaining in the job after duration t for data sets Fa, Fb, Fc, Fd, and Fe. Values observed and predicted by Probability Law I.

values of duration t. For these data sets observed values of the rate of equivalent respondents leaving equivalent jobs, $h_j(t)$, decrease as duration t increases, which accords with the findings of most previous investigators and with my predictions in Section 3.4.

According to the results of Epstein's (1960a: 85-86; 1960b) χ^2 test for these fifteen data sets, if Probability Law I describes the process of individuals leaving jobs, then the probability of obtaining values of χ^2 in a random sample as large as those observed is less than 0.05 for nine data sets (Aa, Ab, Ac, Ba, Ca, Cb, Cc, Ec, Ed) and less than 0.10 for another (Fb). This supports rejection of Probability Law I for these ten data sets. However, Epstein's χ^2 does not indicate that rejection of Probability Law I is warranted for three of the fifteen data sets (Da, Ea, Fa), while too few observations prevented the use of Epstein's χ^2 test for two others (Eb, Fc).

On the basis of visual comparison of observed and predicted curves of $G_j(t)$ versus duration t, Probability Law I can not be rejected for six data sets (Bb, Db, Dc, Ee, Fd, Fe). Acceptance of Probability Law I for these six data sets implies that $h_j(t)$ is independent of duration t and equals κ^*. The conclusion that Probability Law I can not be rejected for these six data sets is supported by Epstein's χ^2 test for one data set (Dc) but not for two others (Bb, Db). Epstein's χ^2 test was not used with the remaining three data sets (Ee, Fd, Fe) because of an insufficient number of observations.

Further evidence concerning the ability of Probability Law I to predict the observations in the twenty-one data sets is indirectly furnished by the findings concerning the other probability laws. If for a particular data set Probability Law I satisfactorily describes

the process of individuals leaving jobs, then for this data set the maximum likelihood estimate of parameters should reduce every other probability law to Probability Law I. If Probability Law I is not satisfactory for a given data set, then the maximum likelihood estimate of parameters for some other probability law should give a maximum likelihood larger than L_I^*, the maximum likelihood of Probability Law I, and should also give a predicted curve that fits the observed curve of $G_j(t)$ versus duration t better than the curve predicted by Probability Law I.

7.2 Findings concerning Probability Law II

Table 7.3 reports values of the maximum likelihood estimate of parameters and other statistics pertinent to Probability Law II for the twenty-one data sets studied. Figures 7.7 through 7.12 display plots of the observed curves of $G_j(t)$ versus duration t and of the corresponding curves predicted by Probability Law II with δ^* and Θ^*.

For three data sets (Dc, Ee, Fe) the maximum likelihood estimate of parameters reduced Probability Law II to Probability Law I (cf. Table 7.3). In addition, Probability Law II is nearly reduced to Probability Law I for three other data sets (Db, Fd, Bc). This is indicated by the fact that $h_j(0) = \delta^*/\Theta^*$ is approximately equal to κ^* and by the large magnitude of Θ^*, which implies that $h_j(t)$ declines so slowly that it is nearly constant over observed values of duration t.

Furthermore, for data sets Db and Fd the maximum likelihood of Probability Law II, L_{II}^*, is less than 10 percent larger than L_I^*, the maximum likelihood of Probability Law I, and the average probability of an observation in these two data sets is less than 1 percent greater for Probability Law II than I on the basis of the $n_j(0)^{th}$ root of

Table 7.3 Statistics pertaining to maximum likelihood parameter estimates for Probability Law II[2].

Data set	$n_j(0)$	δ^*	θ^*	S^*_{II}	S^*_{II}/S^*_I	$-\ln L^*_{II}$	L^*_{II}/L^*_I	$n_j(0)^{th}$ root of L^*_{II}/L^*_I
Aa	42	3.955	1.614	.119	.54	14.968	14.	1.06
Ab	71	2.592	1.667	.144	.39	67.076	54.E+01	1.09
Ac	57	1.681	1.218	.116	.15	68.403	15.E+06	1.34
Ba	83	1.770	1.624	.081	.14	122.742	64.E+04	1.18
Bb	103	7.352	26.669	.037	.40	249.726	2.45	1.01
Ca	130	3.723	4.126	.045	.40	161.088	59.	1.03
Cb	209	1.944	2.873	.049	.12	356.533	54.E+06	1.09
Cc	129	2.276	5.491	.047	.17	271.203	63.E+01	1.05
Da	22	2.858	4.735	.045	.37	35.916	1.93	1.03
Db	97	35.673	116.173	.092	.94	191.897	1.03	<< 1.01
Dc	71	-	-	-	-	-	-	-
Ea	38	.961	.787	.083	.24	40.121	25.E+01	1.16
Eb	18	.395	.492	.180	.39	30.082	21.	1.18
Ec	39	1.245	3.624	.144	.35	65.841	6.6	1.05
Ed	122	.384	1.005	.753	.54	218.148	25.E+11	1.26
Ee	24	-	-	-	-	-	-	-
Fa	41	.504	.736	.204	.22	59.206	16.E+04	1.34
Fb	170	.357	1.231	1.827	1.24	271.979	20.E+11	1.18
Fc	38	.357	1.332	.555	.86	50.052	81.	1.12
Fd	24	2.896	30.615	.206	1.02	38.387	1.07	< 1.01
Fe	32	-	-	-	-	-	-	-

[2]Blanks indicate that the maximum likelihood estimate of parameters reduced the probability law to Probability Law I.

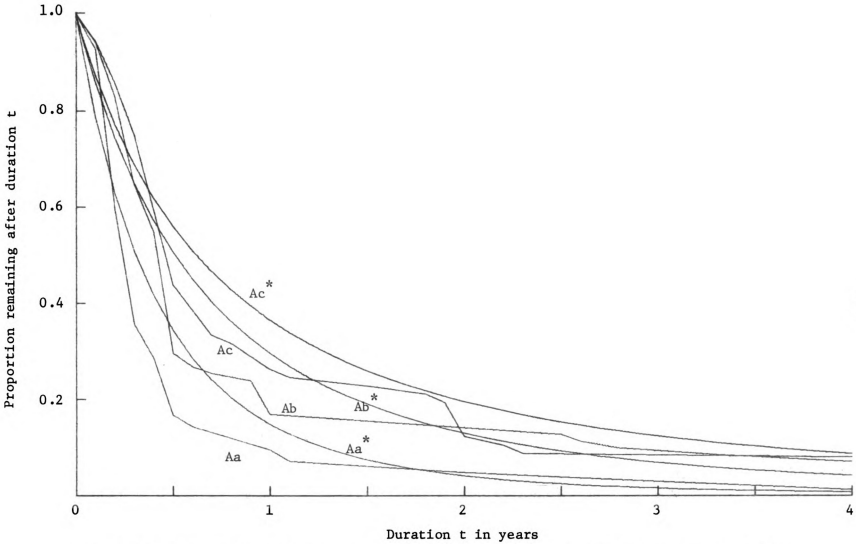

Figure 7.7 Proportion remaining in the job after duration t for data sets Aa, Ab, and Ac. Values observed and predicted by Probability Law II.

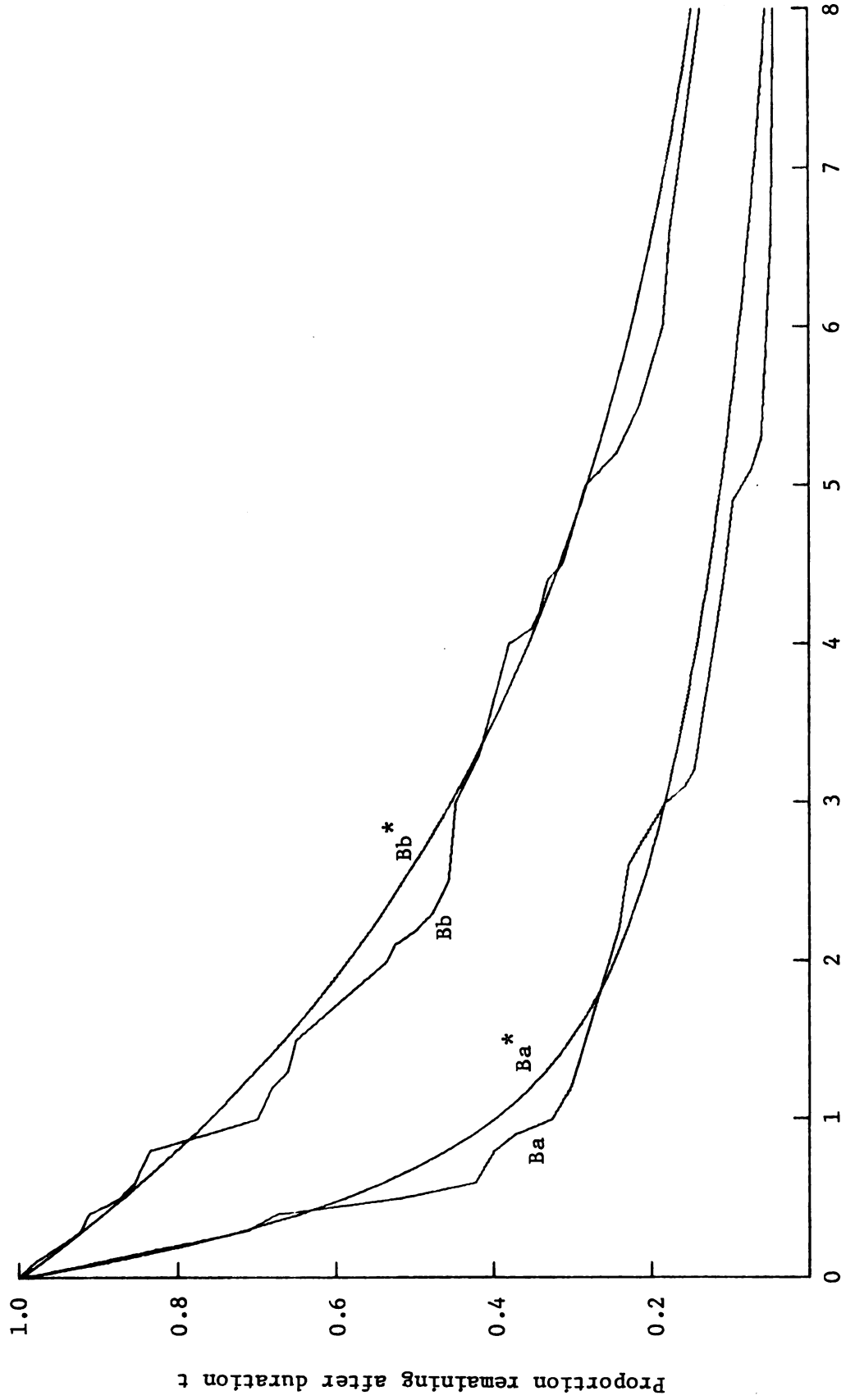

Figure 7.8 Proportion remaining in the job after duration t for data sets Ba and Bb.
Values observed and predicted by Probability Law II.

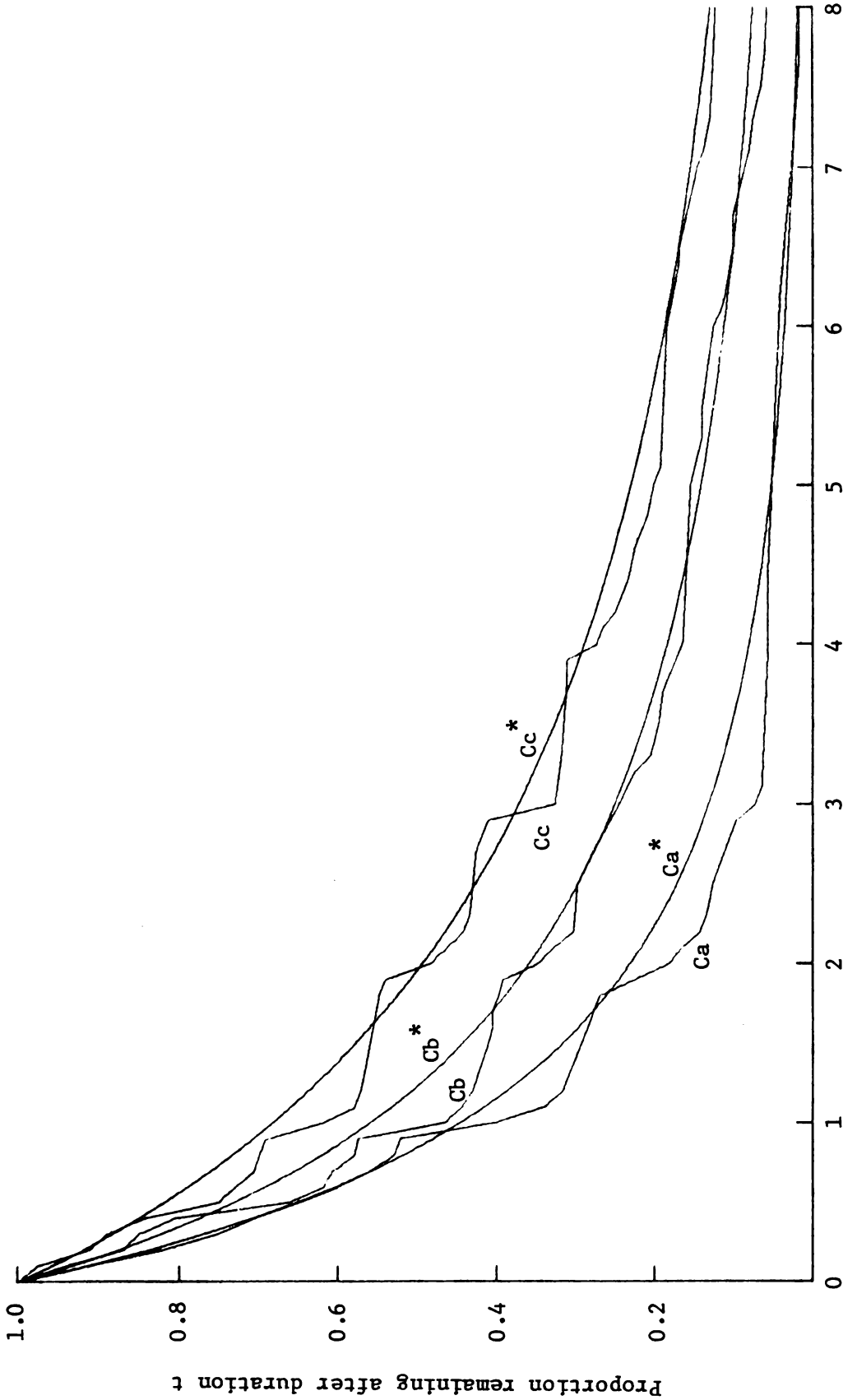

Figure 7.9 Proportion remaining in the job after duration t for data sets Ca, Cb, and Cc. Values observed and predicted by Probability Law II.

1.0

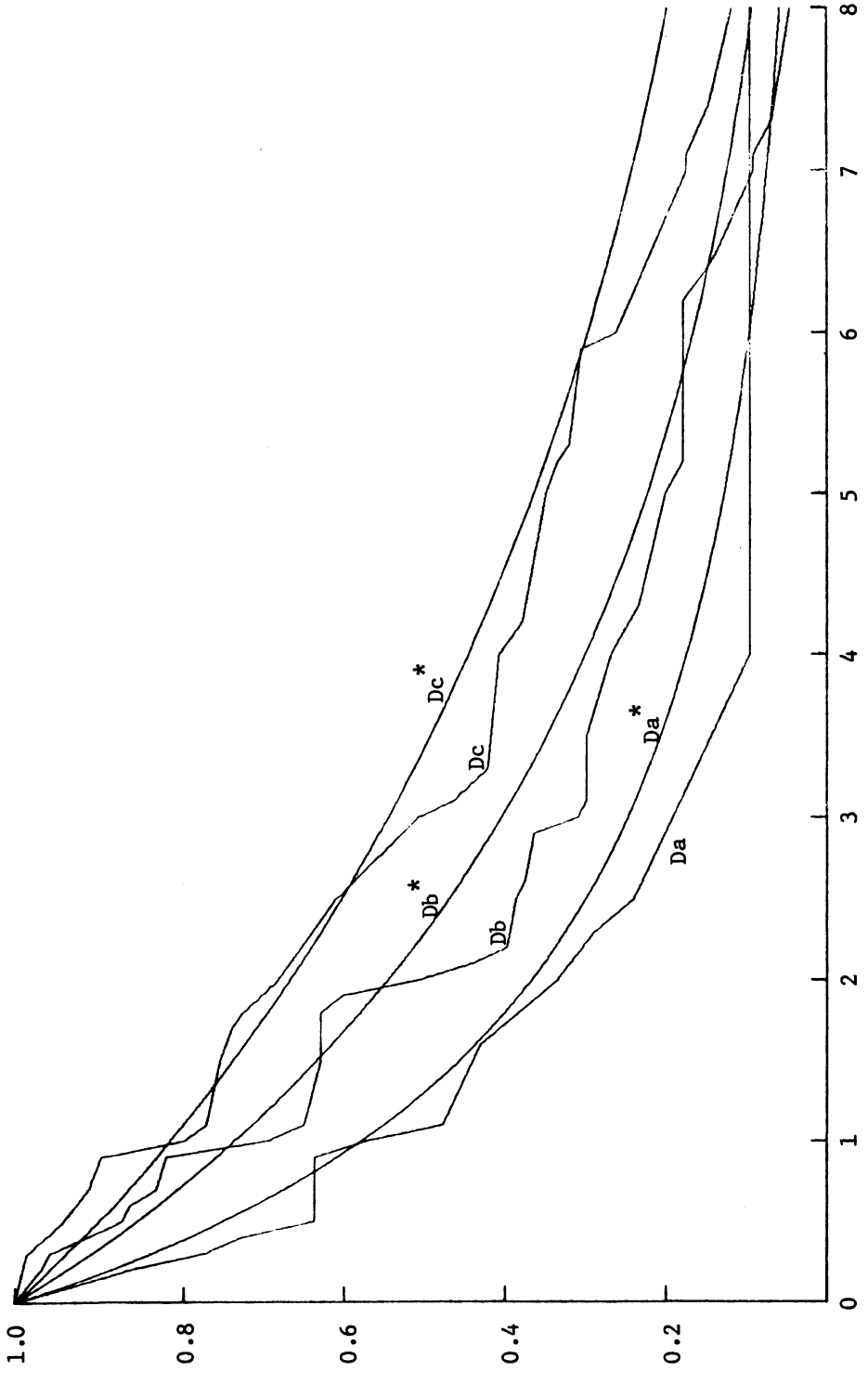

Figure 7.10 Proportion remaining in the job after duration t for data sets Da, Db, and Dc. Values observed and predicted by Probability Law II.

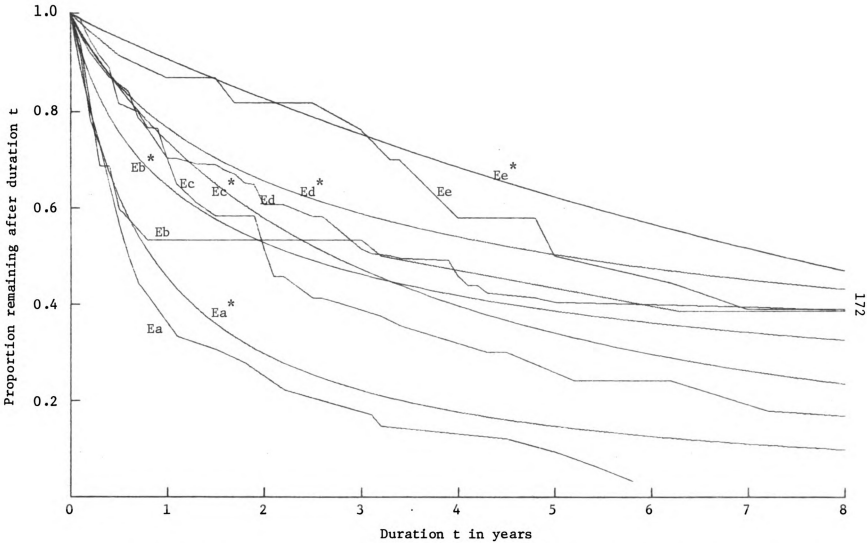

Figure 7.11 Proportion remaining in the job after duration t for data sets Ea, Eb, Ec, Ed, and Ee. Values observed and predicted by Probability Law II.

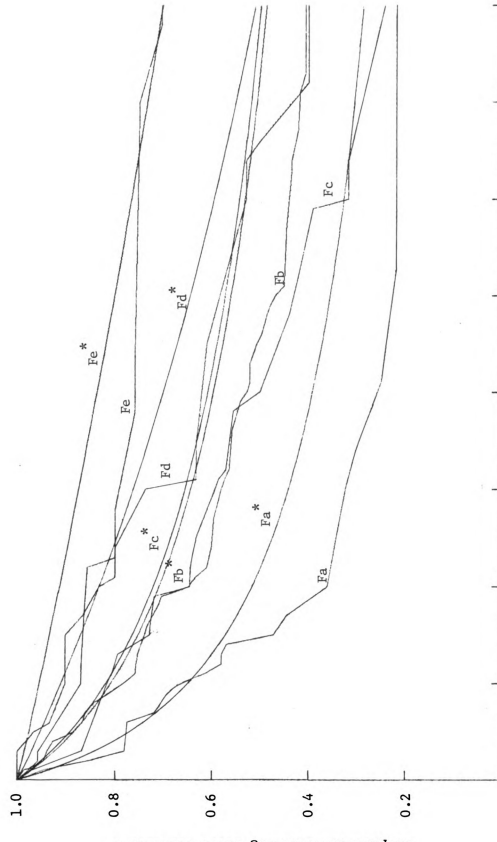

Figure 7.12 Proportion remaining in the job after duration t for data sets Fa, Fb, Fc, Fd, and Fe. Values observed and predicted by Probability Law II.

L^*_{II}/L^*_I. Hence it is not surprising that S^*_{II}/S^*_I, the ratio of the sum of the squares of the deviation between observed and predicted values of $G_j(t)$ for the two probability laws, is approximately 1.0 for these two data sets and that the curves predicted by Probability Laws I and II for these data sets are visually almost indistinguishable. This implies that Probability Law II offers no significant improvement over Probability Law I for data sets Db and Fd.

However, inspection of the plots in Figures 7.2 and 7.8 discloses that for data set Bc Probability Law II predicts the observed curve of $G_j(t)$ versus duration t noticeably better than Probability Law I. This judgment is corroborated by a value of 0.40 for S^*_{II}/S^*_I for data set Bc, which indicates a substantial reduction in the sum of the squares of the deviation between observed and predicted values of $G_j(t)$. Moreover L^*_{II} is more than twice as great as L^*_I even though the average probability of an observation in this data set is only 1 percent greater for Probability Law II than I on the basis of the $n_j(0)^{th}$ root of L^*_{II}/L^*_I. I conclude that I erred in originally accepting Probability Law I for data set Bc and that the rejection of Probability Law I indicated by Epstein's χ^2 test for this data set was correct.

On the basis of visual comparison of the observed and predicted curves in Figures 7.7 through 7.12, Probability Law II predicts the observed curves relatively well for the remaining fifteen data sets (Aa, Ab, Ac, Ba, Ca, Cb, Cc, Da, Ea, Eb, Ec, Ed, Fa, Fb, Fc). And, although the curves predicted by Probability Law II for data sets Aa, Ab, Ac, and Eb do not decline quite as rapidly as the corresponding observed curves and are therefore not entirely satisfactory, the observations in all fifteen data sets are predicted better by Probability

Law II than I. This conclusion is based on the magnitude of L^*_{II}/L^*_I, which measures the relative ability of Probability Laws I and II to predict all $n_j(0)$ observations in a data set, and by the magnitude of the $n_j(0)^{th}$ root of L^*_{II}/L^*_I, which measures the relative ability of Probability Laws I and II to predict a single observation on the average.

In addition, the ratio S^*_{II}/S^*_I is considerably less than 1.0 for fourteen of these fifteen data sets, which supports my judgment that Probability Law II predicts the observed curve of $G_j(t)$ versus duration t better than Probability Law I. However, this ratio is greater than 1.0 for data set Fb, apparently because the observations in this data set are predicted much better by Probability Law I than II for large values of duration t, even though the converse is true for small values of duration t. Since values of $G_j(t)$ become increasingly less accurate as duration t increases, it would be improper to prefer Probability Law I over II on the basis of S^*_{II}/S^*_I for this data set.

7.3 Findings concerning Probability Law IV

Table 7.4 exhibits values of the maximum likelihood estimate of parameters along with other statistics relating to Probability Law IV for the twenty-one data sets examined in this research. Note that the maximum likelihood estimate of parameters reduced Probability Law IV to Probability Law I for the same three data sets (Dc, Ee, Fe) for which Probability Law II was reduced to Probability Law I. And, like Probability Law II, Probability Law IV is nearly reduced to Probability Law I for two other data sets (Db, Fd). This is indicated by the fact that $h_j(0) = \xi^* + \omega^*$ is approximately equal to κ^* and by the small magnitude of ω^*, which implies that $h_j(t)$ declines very slowly over the observed

Table 7.4 Statistics pertaining to maximum likelihood parameter estimates for Probability Law IV[3].

Data set	$n_j(0)$	ξ^*	ω^*	ϕ^*	S^*_{IV}	S^*_{IV}/S^*_I	$-\ln L^*_{IV}$	L^*_{IV}/L^*_I	$n_j(0)^{th}$ root of L^*_{IV}/L^*_I
Aa	42	.448	2.104	.737	.106	.48	14.581	21.	1.08
Ab	71	.372	1.309	.864	.123	.33	65.960	45.E+02	1.11
Ac	57	.090	1.282	.542	.082	.11	66.974	64.E+06	1.37
Ba	83	.189	.927	.636	.066	.11	121.754	17.E+05	1.19
Bb	103	.158	.126	.121	.034	.37	249.641	2.67	1.01
Ca	130	.079	.822	.214	.039	.35	160.638	92.	1.04
Cb	209	.158	.523	.399	.046	.12	356.423	61.E+06	1.09
Cc	129	.147	.297	.353	.046	.17	270.505	13.E+02	1.06
Da	22	.227	.390	.363	.044	.36	35.887	1.93	1.03
Db	97	.227	.081	.037	.092	.94	191.897	1.03	<< 1.01
Dc	71	-	-	-	-	-	-	-	-
Ea	38	.000	1.182	.678	.082	.23	38.857	90.E+01	1.20
Eb	18	.059	1.053	2.131	.116	.25	26.641	65.E+01	1.43
Ec	39	.104	.104	.534	.155	.38	65.308	11.	1.06
Ed	122	.022	.313	.452	.805	.58	216.072	20.E+12	1.28
Ee	24	-	-	-	-	-	-	-	-
Fa	41	.017	.559	.508	.210	.22	58.065	52.E+04	1.38
Fb	170	.015	.242	.372	2.079	1.41	269.734	20.E+12	1.20
Fc	38	.000	.203	.225	.564	.88	49.660	12.E+01	1.13
Fd	24	.000	.094	.028	.206	1.02	38.383	1.08	< 1.01
Fe	32	-	-	-	-	-	-	-	-

[3]For data sets Ea, Fc, and Fd ξ^* appeared to converge to a negative number, which is illegitimate. I have therefore reported ω^* and ϕ^* for ξ^* fixed at zero, its lowest legitimate value.

values of duration t. Since L^*_{IV} is less than 10 percent greater than L^*_I, and since the $n_j(0)^{th}$ root of L^*_{IV}/L^*_I is less than 1.01 for both data sets, it appears that Probability Law IV offers no significant improvement over Probability Law I for data sets Db and Fd.

Insofar as the remaining sixteen data sets are concerned, a comparison of Tables 7.3 and 7.4 indicates that Probability Law IV predicts observations consistently, but only slightly, better than Probability Law II. This conclusion is based on a comparison of the ratios L^*_{IV}/L^*_I and L^*_{II}/L^*_I and of the $n_j(0)^{th}$ roots of L^*_{IV}/L^*_I and L^*_{II}/L^*_I. Probability Law IV improves markedly upon Probability Law II only for data set Eb. Consequently the plots of observed curves of $G_j(t)$ versus duration t and the corresponding curves predicted by Probability Law IV supply little new information and are omitted from this report.

7.4 Findings concerning Probability Law V

Table 7.5 gives the values of the maximum likelihood estimate of parameters as well as other statistics pertaining to Probability Law V for the twenty-one data sets examined. Figures 7.13 through 7.18 show the plots of the observed curves of $G_j(t)$ versus duration t and of the corresponding curves predicted by Probability Law V with β^*, λ^*_1, and λ^*_2.

As with Probability Laws II and IV, the maximum likelihood estimate of parameters reduced Probability Law V to Probability Law I for data sets Dc and Ee (cf. Table 7.5). Furthermore, like Probability Laws II and IV, Probability Law V predicts data sets Db and Fd only slightly better than Probability Law I on the basis of values of L^*_V/L^*_I and its $n_j(0)^{th}$ root. Improvement in the prediction of observations in these data sets with Probability Law II, IV, or V does not seem great

Table 7.5 Statistics pertaining to maximum likelihood parameter estimates for Probability Law V.[4]

Data set	$n_j(0)$	β^*	λ_1^*	λ_2^*	S_V^*	S_V^*/S_I^*	$-\ln L_V^*$	L_V^*/L_I^*	$n_j(0)^{th}$ root of L_V^*/L_I^*
Aa	42	.887	2.855	.453	.077	.35	13.245	79.	1.11
Ab	71	.753	2.174	.359	.092	.25	64.140	10.E+03	1.14
Ac	57	.881	1.419	.099	.066	.09	65.423	30.E+07	1.41
Ba	83	.635	1.749	.238	.047	.08	121.212	30.E+05	1.20
Bb	103	.577	.368	.161	.033	.35	249.586	2.82	1.01
Ca	130	.893	.966	.152	.027	.24	159.154	41.E+01	1.05
Cb	209	.615	.974	.190	.045	.11	356.268	71.E+06	1.09
Cc	129	.553	.641	.148	.047	.17	270.457	13.E+02	1.06
Da	22	.641	.786	.225	.046	.38	35.880	2.00	1.03
Db	97	.548	.362	.246	.090	.92	191.889	1.04	<< 1.01
Dc	71	-	-	-	-	-	-	-	-
Ea	38	.813	1.246	.000	.087	.25	38.529	12.E+02	1.21
Eb	18	.404	2.605	.058	.106	.23	26.400	83.E+01	1.45
Ec	39	.416	.786	.102	.145	.36	65.167	13.	1.07
Ed	122	.497	.594	.022	.791	.57	215.833	26.E+12	1.29
Ee	24	-	-	-	-	-	-	-	-
Fa	41	.658	.775	.019	.197	.21	57.854	64.E+04	1.39
Fb	170	.463	.505	.016	2.053	1.39	269.358	28.E+12	1.20
Fc	38	.593	.305	.000	.542	.84	49.645	12.E+01	1.13
Fd	24	.853	.108	.000	.203	1.00	38.371	1.09	< 1.01
Fe	32	.099	.730	.035	.559	1.16	57.003	1.97	1.02

[4]For data sets Ea, Fc, and Fd λ_2^* appeared to converge to a negative number, which is illegitimate. I have therefore reported β^* and λ_1^* for λ_2^* fixed at zero, its lowest legitimate value.

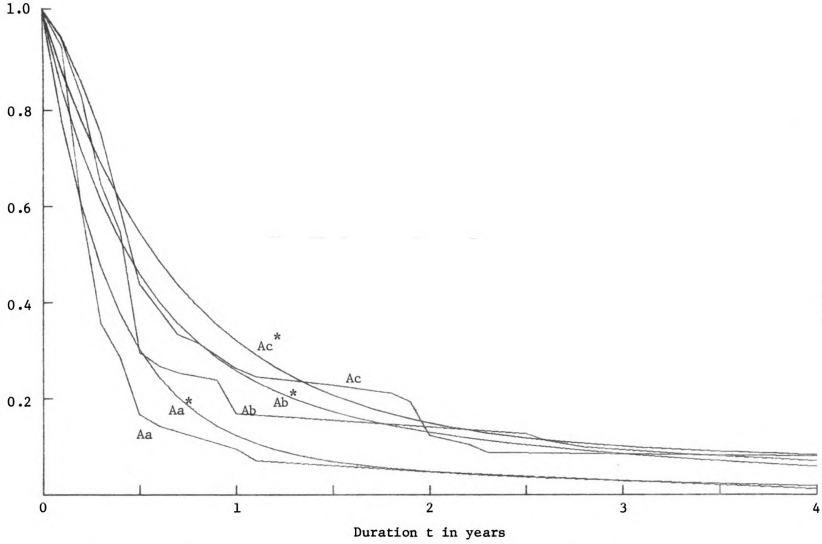

Figure 7.13 Proportion remaining after duration t for data sets Aa, Ab, and Ac. Values observed and predicted by Probability Law V.

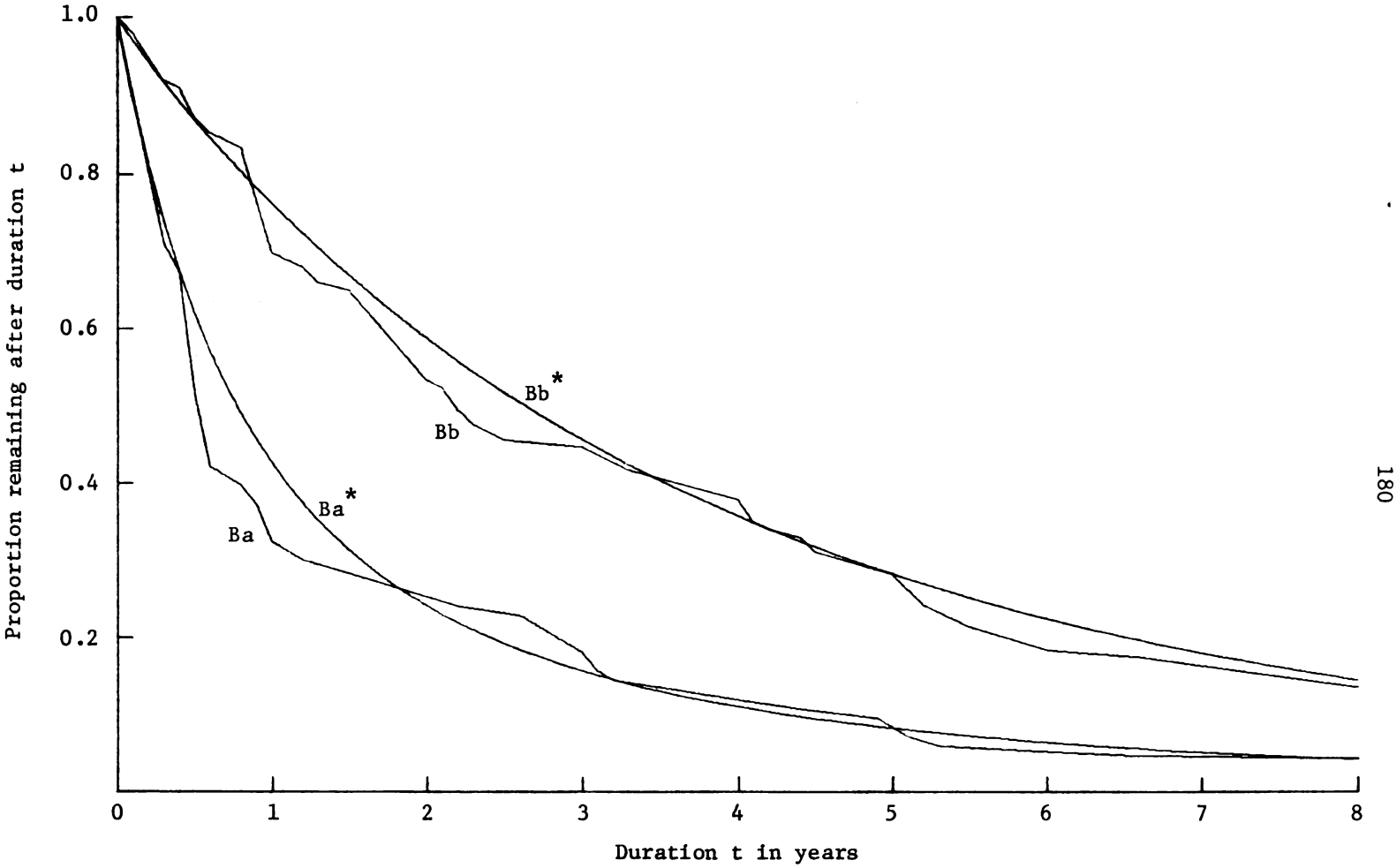

Figure 7.14 Proportion remaining in the job after duration t for data sets Ba and Bb. Values observed and predicted by Probability Law V.

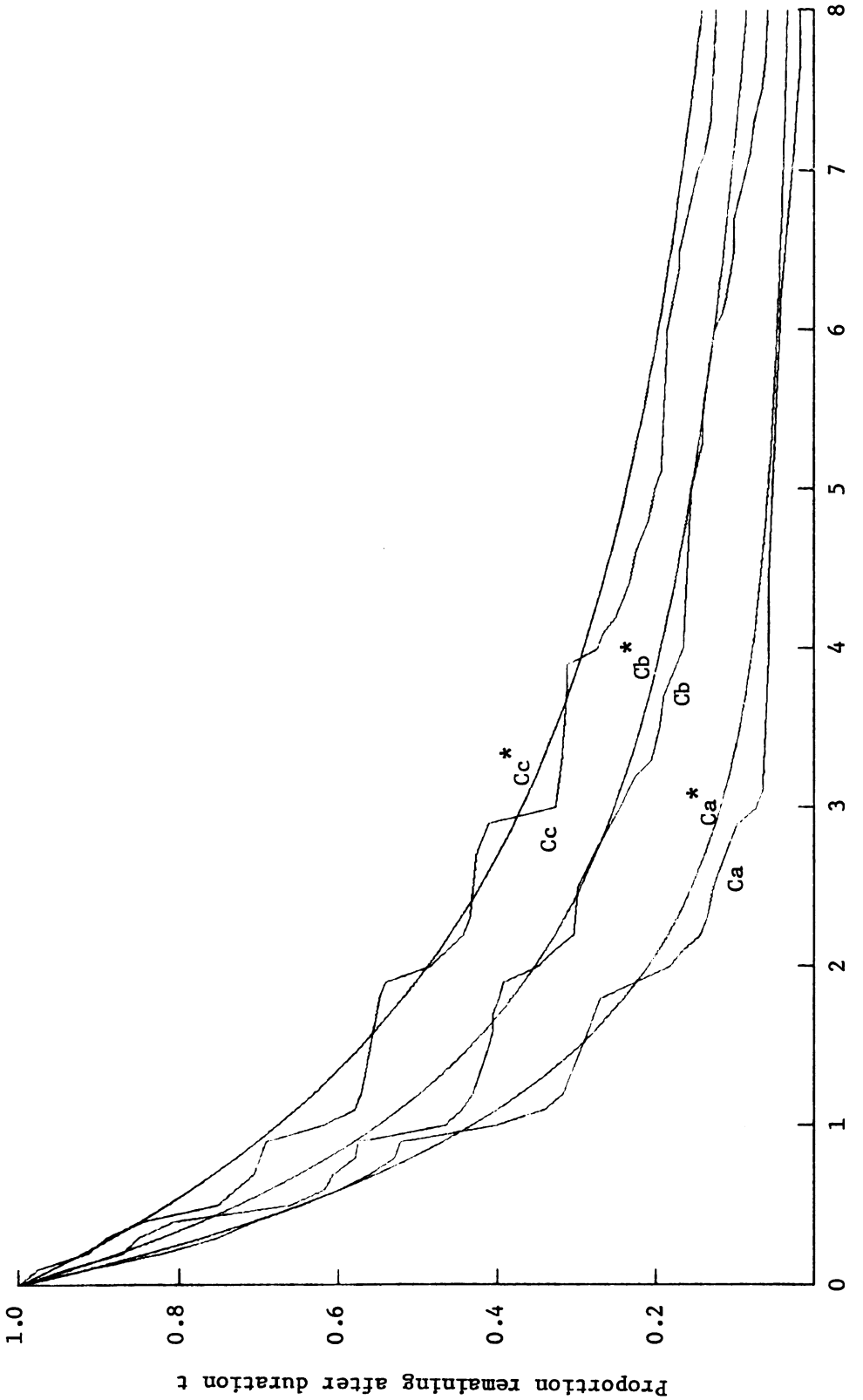

Figure 7.15 Proportion remaining in the job after duration t for data sets Ca, Cb, and Cc. Values observed and predicted by Probability Law V.

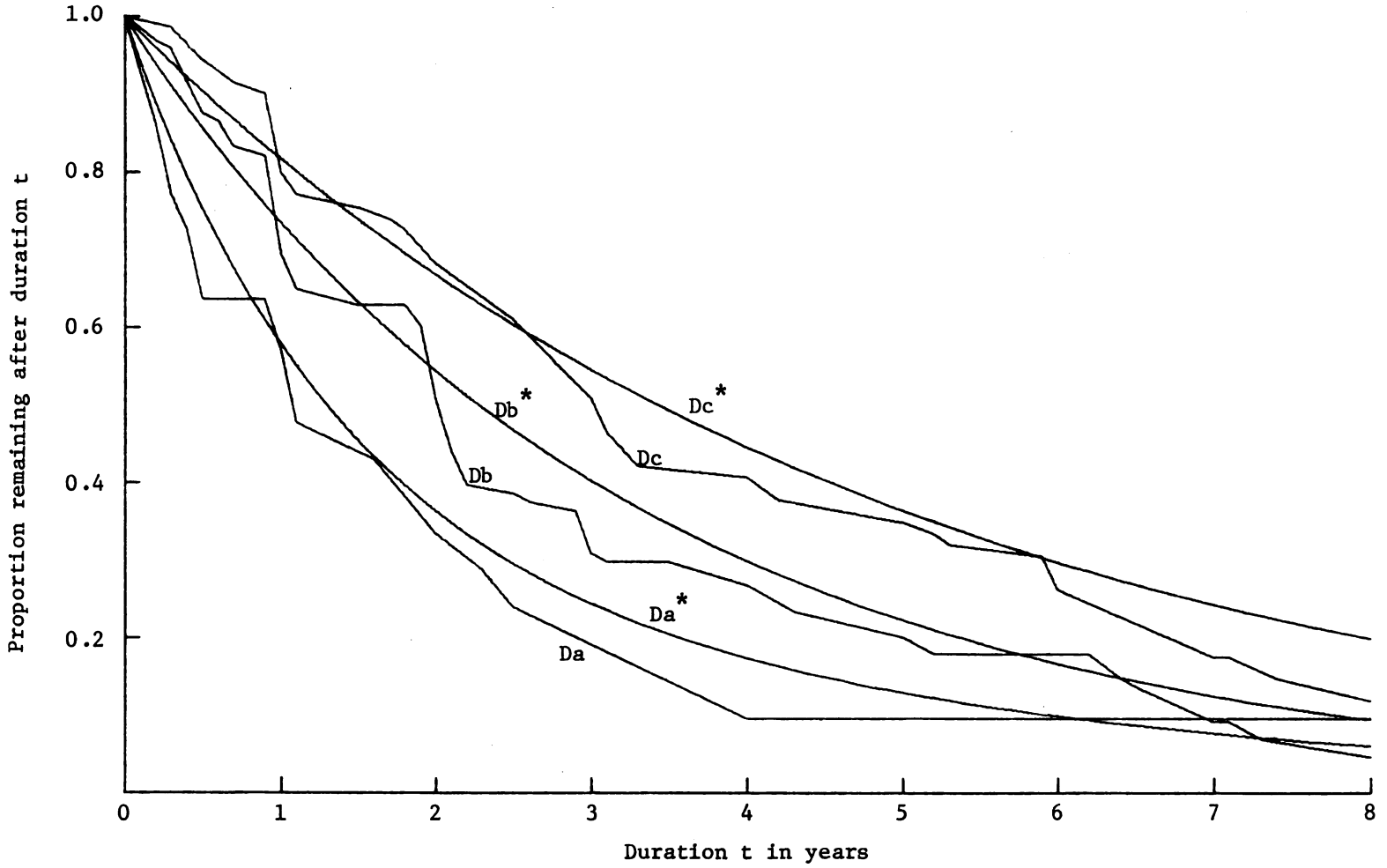

Figure 7.16 Proportion remaining in the job after duration t for data sets Da, Db, and Dc. Values observed and predicted by Probability Law V.

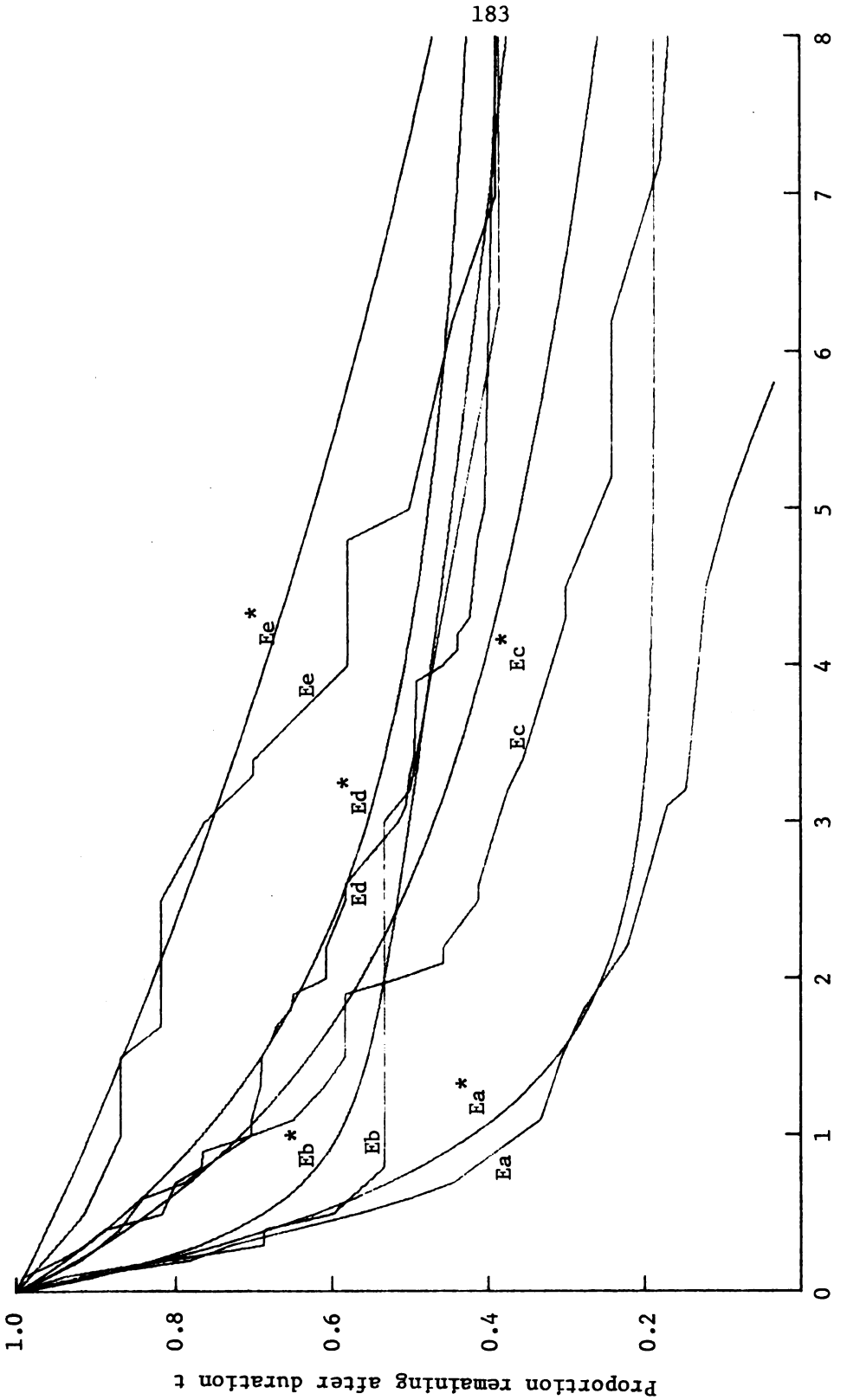

Figure 7.17 Proportion remaining in the job after duration t for data sets Ea, Eb, Ec, Ed, and Ee. Values observed and predicted by Probability Law V.

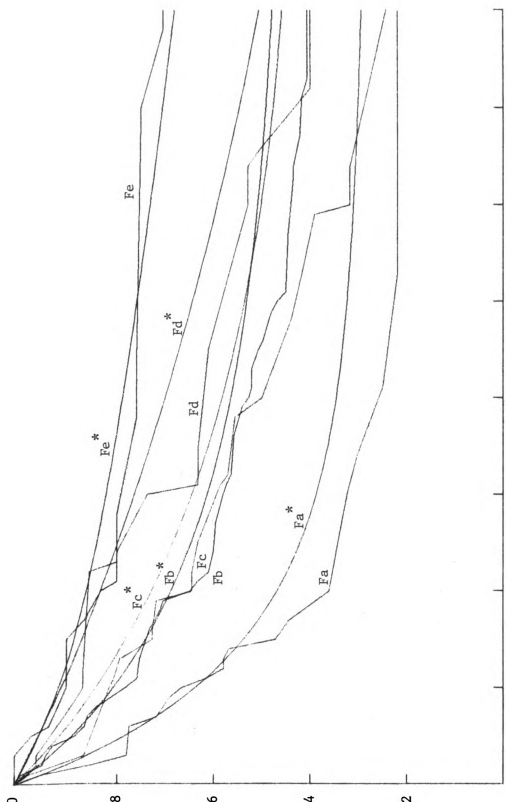

Figure 7.18 Proportion remaining in the job after duration t for data sets Fa, Fb, Fc, Fd, and Fe. Values observed and predicted by Probability Law V.

enough to justify rejection of Probability Law I for any of these four data sets.

On the other hand, unlike Probability Laws II and IV, Probability Law V was not reduced to Probability Law I for data set Fe. While the improvement in the prediction of observations in this data set is small according to the values of L_V^*/L_I^* and its $n_j(0)^{th}$ root, it is quite possibly not negligible.

Values of L_V^*/L_I^* and its $n_j(0)^{th}$ root indicate that Probability Law V predicts observations in the remaining sixteen data sets (Aa, Ab, Ac, Ba, Bb, Ca, Cb, Cc, Da, Ea, Eb, Ec, Ed, Fa, Fb, Fc) consistently better than Probability Laws II and IV although the improvement is generally not great. Most values of S_V^*/S_I^* also support this conclusion. Visual examination of the plots in Figures 7.13 through 7.18 suggests that Probability Law V adequately predicts the observed survival curves for these sixteen data sets, excluding possibly data sets Aa, Ab, and Ac. Moreover, on the basis of visual comparison the observed survival curves for all sixteen data sets are predicted by Probability Law V as well as, and usually better than, Probability Laws II and IV.

7.5 Findings concerning Probability Laws VI and VII

The procedure used in this study to determine the maximum likelihood estimate of parameters reduced Probability Law VII, which closely resembles Probability Law V (cf. equations (2.71) and (2.84)), to either Probability Law I or V for all twenty-one data sets examined. This should not greatly surprise us as a visual examination of plots of observed and predicted curves indicates that either Probability Law I or V satisfactorily predicts the observed survival curves for all

data sets with the possible exception of Aa, Ab, and Ac. Even for these data sets the predicted curves are fairly close to the observed curves.

When Probability Law V predicts an observed set of data relatively well, it is difficult to find initial parameter estimates for Probability Law VII which give a value of the likelihood L^*_{VII} greater than L^*_V, an apparently necessary condition with the procedure that I used in order to find a maximum likelihood estimate of parameters that does not reduce Probability Law VII to V. Because Probability Law VII has five independent parameters, trying all relatively reasonable combinations of initial parameter estimates is a tedious process that was not fully explored in this study. Therefore for some data sets examined there may exist a maximum likelihood estimate of parameters that does not reduce Probability Law VII to V. At present no stronger statement is permissible.

Mathematically Probability Law VI closely resembles Probability Law VII, possessing four exponential terms in the expression for $\bar{G}_j(t)$ rather than three (cf. equations (2.81) and (2.84)). Since I was unable to find a maximum likelihood estimate of parameters that did not reduce Probability Law VII to either Probability Law I or V, an attempt to find a maximum likelihood estimate of parameters that did not reduce Probability Law VI to either Probability Law I, V, or VII seemed certain to fail and was therefore not undertaken.

7.6 Discussion

Previous investigators have repeatedly reported that their predictions of social mobility based on Probability Law I were unsatisfactory. My findings concur with this conclusion for seventeen of the twenty-one

data sets that I examined, but not for four others (Db, Dc, Ee, Fd). Note that the observed curves for the four data sets adequately predicted by Probability Law I are among those declining most slowly as duration t increases. With more accurate determination of the survival curves for large values of duration t, e.g., more than ten years, Probability Law I might not appear nearly as satisfactory as in the present study.

For the other seventeen data sets, predictions based on Probability Law II, IV, or V, and usually all three, markedly improve upon the predictions based on Probability Law I. At the same time I was unable to find a maximum likelihood estimate of parameters that did not reduce Probability Law VII, and by inference Probability Law VI, to Probability Law V. My findings for these seventeen data sets do not indicate whether Probability Law II, IV, or V is the best alternative to Probability Law I, although the evidence consistently suggests that Probability Law IV is a slightly better predictor than II, and that V is a slightly better predictor than either II or IV.

Because of the difficulty of distinguishing among Probability Laws II, IV, and V on the basis of their ability to predict the observed rate at which apparently equivalent respondents left equivalent jobs, it is worth trying to distinguish among them by comparing known models from which they can be derived (cf. Chapter 2). Since I lack data permitting empirical evaluation of alternative models leading to the same probability law, interpreting the probability laws in terms of models from which they can be derived illustrates rather than tests these models. Nevertheless, these illustrations are worth examining because the parameter values for a particular model should accord with the

substantive arguments made in Chapter 3. In particular, the dependence of the parameters of a given model on attributes of jobs and respondents (e.g., occupational category and educational level) should reflect the hypotheses previously made about the effect of these variables on the process of an individual leaving a job.

Usually one can determine the nature of the dependency of the parameters of a model on some attribute of jobs or persons better if one can order and compare the results for more than two values of the attribute. This criterion suggests that we compare the effect of educational level on models of respondents leaving a job as a migratory farm laborer in Michigan, nonfarm laborer in Michigan or Texas, or nonmigratory farm laborer in Michigan or Texas. The third job category is not an acceptable choice because the maximum likelihood estimate of parameters reduced Probability Laws II, IV, and V to Probability Law I for two of the three data sets in this category. The second job category seems a better selection than the first because the number of observations, and presumably the accuracy of the parameter estimates, is greater for the data sets for this job (Ca, Cb, Cc).

Comparing these data sets is still far from ideal because of the possible increase in the rate of leaving the job during 1960-1967. Lack of a better alternative necessitates that this complication be ignored in the calculations and discussion that follows, but the uncertainty that it introduces should not be disregarded.

Probability Laws II, IV, and V can each be derived from models constructed through the use of Approach A, the assumption of nonstationarity, and Approach B, the assumption of heterogeneity. In addition, Probability Law V can be derived from a model constructed through

the use of Approach C, the assumption of stages within a social position. The discussion that follows treats all seven of these models both from a general point of view and in terms of their implications for the effect of educational level on the process of respondents leaving a job as a nonfarm laborer, i.e., for data sets Ca, Cb, and Cc. Since duration rather than calendar year or an individual's age seemed to be the measure of time most influencing the rate at which respondents left their jobs, in all seven models time t is conceptualized as the duration in job j.

Models based on Approach A postulate that the instantaneous rate of equivalent individuals leaving equivalent jobs j, $h_j(t)$, depends on time t according to some specified mathematical function. If one postulates that

$$(7.1) \qquad h_j(t) = \delta/(\Theta + t) = (\delta/\Theta)(1 + t/\Theta)^{-1},$$

which I designate Model A.II, then one obtains Probability Law II. If one postulates that

$$(7.2) \qquad h_j(t) = \xi + \omega \exp[-\Phi t],$$

which I designate Model A.IV, then one obtains Probability Law IV. If one postulates that

$$(7.3) \qquad h_j(t) = \frac{\beta \lambda_1 \exp[-\lambda_1 t] + (1 - \beta) \lambda_2 \exp[-\lambda_2 t]}{\beta \exp[-\lambda_1 t] + (1 - \beta) \exp[-\lambda_2 t]},$$

which I designate Model A.V, then one obtains Probability Law V.

These equations permit the calculation of values of $h_j(t)$ after any duration t for initially equivalent individuals in equivalent jobs. The values of $h_j(t)$ after duration zero and infinity are of special

interest. Model A.II implies that $h_j(0)$ is δ/Θ and that $h_j(\infty)$ is zero. Model A.IV implies that $h_j(0)$ is $\xi + \omega$ and that $h_j(\infty)$ is ξ. Model A.V implies that $h_j(0)$ is $\beta\ \lambda_1 + (1 - \beta)\ \lambda_2$ and that $h_j(\infty)$ is λ_2 whenever $\lambda_1 >> \lambda_2$.

Because all three probability laws give nearly the same predicted values of the proportion remaining in a job after duration t for any given data set, values of $h_j(0)$ predicted by Models A.II, A.IV, and A.V should be very similar for any particular data set. The models should predict $h_j(\infty)$ less precisely than $h_j(0)$ because of the relatively small number of respondents remaining in the job after long durations; nevertheless, the three models should agree fairly closely in predicted values of $h_j(\infty)$ for a particular data set.

Inspection of Table 7.6 reveals that for data sets Ca, Cb, and Cc, values of $h_j(0)$ vary only slightly among Models A.II, A.IV, and A.V. Furthermore, for all three models $h_j(0)$ increases as educational level increases. This fits with my hypothesis in Section 3.3 that a jobholder's dissatisfaction with any given job j increases as his educational level increases, but it does not enable us to differentiate among the three models. On the other hand, while values of $h_j(\infty)$ for a given data set do not vary greatly between Models A.IV and A.V, the nature of the effect of educational level on $h_j(\infty)$ is inconclusive, presumably because of the imprecision of the calculated values.

The rate at which $h_j(t)$ decreases from its highest to lowest value is a third quantity of particular interest in models based on Approach A. Equations (7.1) and (7.2) indicate that this rate increases as Θ decreases for Model A.II and as Φ increases for Model A.IV. However, this rate does not depend on the parameters of Probability Law V in any

Table 7.6 Values of $h_j(0)$ and $h_j(\infty)$ calculated for data sets Ca, Cb, and Cc using Models A.II, A.IV, and A.V and the corresponding maximum likelihood estimates of parameters.

Values of $h_j(0)$

Data set	Model A.II	Model A.IV	Model A.V
Ca	.902	.901	.879
Cb	.677	.681	.672
Cc	.414	.444	.421

Values of $h_j(\infty)$

Data set	Model A.II	Model A.IV	Model A.V
Ca	.000	.079	.152
Cb	.000	.158	.190
Cc	.000	.147	.148

simple fashion for Model A.V.

Tables 7.3 and 7.4 show that values of Θ^* and Φ^* for data sets Ca, Cb, and Cc do not monotonically increase, decrease, or remain unchanged as the educational level of nonfarm laborers increases. I did not anticipate this curvilinear variation in the rate at which $h_j(t)$ decreases from its highest to lowest value as the educational level of nonfarm laborers increases, nor have I any satisfactory substantive explanation for it.

At present there are no substantive reasons for preferring one of these three models over the other two. However, known usefulness in other areas of science and mathematical simplicity are advantages for a model. Judged in this light, the mathematical complexity of equation (7.3) makes Model A.V seem an umpromising route to an explanation of the process of individuals leaving a job j. The known utility of the exponential function for describing monotonically decreasing quantities suggests that Model A.IV has a greater potential than Model A.II of

developing into such an explanation.

Models based on Approach B, the assumption of heterogeneity, postulate that the probability density function $c_j(y,0)$ describes the distribution of equivalent individuals in equivalent jobs j after duration 0, that the instantaneous rate of an individual leaving job j depends on his position on variable y and possibly on duration t, $h_j(y,t)$, and that an individual's position on y does not change during his stay in job j. If one postulates that

$$h_j(y,t) = y, \tag{7.4}$$

$$c_j(y,0) = \Theta^{\delta} y^{\delta-1} \exp[-\Theta y]/(\delta - 1)! , \tag{7.5}$$

$y \geq 0$, which I designate Model B.II, then one obtains Probability Law II. If one postulates that

$$h_j(y,t) = \xi + \Phi y, \tag{7.6}$$

$$c_j(y,0) = (\omega/\Phi)^y \exp[-\omega/\Phi]/y! , \tag{7.7}$$

$y = 0, 1, 2, \ldots$, which I designate Model B.IV, then one obtains Probability Law IV. If one postulates that

$$h_j(y_1,t) = \lambda_1, \tag{7.8}$$

$$c_j(y_1,0) = \beta, \tag{7.9}$$

$$h_j(y_2,t) = \lambda_2, \tag{7.10}$$

$$c_j(y_2,0) = (1 - \beta), \tag{7.11}$$

which I designate Model B.V, then one obtains Probability Law V.

Unlike the three models based on Approach A, the three models based on Approach B specify that $h_j(y,t)$ is independent of time. In other words, these models assume that the instantaneous rate at which

any individual leaves the job is a constant, even though this rate varies among equivalent individuals in equivalent jobs j. Thus these models imply that the decrease in $h_j(t)$ accompanying increases in duration arises solely from initial heterogeneity of the individuals in jobs for any particular data set.

Quantities of particular interest in these models are the mean and variance of the instantaneous rate at which equivalent individuals leave equivalent jobs after duration 0. Model B.II implies that the mean of $h_j(0)$ is δ/Θ and that its variance is δ/Θ^2; Model B.IV implies that the mean of $h_j(0)$ is $\xi + \omega$ and its variance is $\omega\Phi$; Model B.V implies that the mean of $h_j(0)$ is $\beta\lambda_1 + (1 - \beta)\lambda_2$ and its variance is $\beta(1 - \beta)(\lambda_1 - \lambda_2)^2$. Because all three probability laws predict nearly the same values of the proportion remaining in the job after duration t for any given data set, values of the mean and variance of the instantaneous rate at which respondents left the job after duration 0 should not vary much among Models B.II, B.IV, and B.V for a given data set.

Table 7.7 shows that values of the mean of $h_j(0)$ vary only slightly among Models B.II, B.IV, and B.V for data sets Ca, Cb, and Cc. Moreover, for all three models the mean of $h_j(0)$ increases as educational level increases. This agrees with the prediction that dissatisfaction with a given job j increases as the educational level of the jobholder increases, but it does not allow a comparative evaluation of the three models.

Note that for a given probability law, values of the mean of $h_j(0)$ for the model based on Approach B (cf. Table 7.7) are identical to the values of $h_j(0)$ for the model based on Approach A (cf. Table 7.6). Comparison of the general expressions for the two quantities predicted

Table 7.7 Values of the mean and variance of $h_j(0)$ calculated for data sets Ca, Cb, and Cc using Models B.II, B.IV, and B.V and the corresponding maximum likelihood estimates of parameters.

Mean of $h_j(0)$

Data set	Model B.II	Model B.IV	Model B.V
Ca	.902	.901	.879
Cb	.677	.681	.672
Cc	.414	.444	.421

Variance of $h_j(0)$

Data set	Model B.II	Model B.IV	Model B.V
Ca	.219	.176	.063
Cb	.236	.209	.146
Cc	.075	.105	.060

for a given probability law by the two types of models reveals that this is true in general and is not just a chance occurrence for these particular data sets.

Values of the variance of $h_j(0)$ for a given data set (cf. Table 7.7) show considerably more variation among Models B.II, B.IV, and B.V than do the values for the mean of $h_j(0)$. Furthermore, the relationship between educational level and the variance of $h_j(0)$ appears to be curvilinear for all three models. Since the variance provides a measure of the heterogeneity within the data set predicted by the models based on Approach B, the information in Table 7.7 implies that for the job of nonfarm laborer, respondents with four to eight years of completed schooling are more heterogeneous than respondents with greater or fewer years of completed schooling. There are no obvious substantive reasons why this should be true. Possible explanations include inadequate identification of equivalent respondents in equivalent jobs in the first phase of the research, invalidity of the three models

based on Approach B, and random variation.

To date no one has provided any substantive arguments why one of the three models constructed with Approach B is preferable to the other two. The mathematical properties of these three models also give no basis for distinguishing among them: in all three models the expressions defining the instantaneous rate of individuals leaving the job are extremely simple, and the postulated distributions describing heterogeneity are well known and easily manipulated.

A potential problem common to these and other models based on Approach B is the apparent contradiction that equivalent individuals in equivalent jobs are postulated to be heterogeneous from the first moment that an individual enters the job. This contradiction is strictly apparent if variable y refers to an attribute of the relationship between an individual and his job whose value is randomly chosen at the moment that the individual enters the job. The contradiction is genuine if variable y refers to an attribute of individuals or of jobs whose value is established prior to the individual entering the job. Obviously the difficulty which this introduces is not insurmountable, but the restriction on the nature of variable y must be recalled in developing explanatory models based on Approach B.

Models A.II, A.IV, A.V, B.II, B.IV, and B.V have a common and possibly unrealistic property. All six models postulate that the instantaneous rate at which any given individual leaves the job after duration t is determined from the first moment that he enters the job, even though this rate may be unknown to the investigator. Thus these models imply that events occurring randomly after the individual enters his job can not alter the predetermined rate at which he leaves his job

after duration t.

Models constructed through the use of Approach C, the assumption of a finite number of stages within a job and Markovian movement among these stages and from the job, avoid many problems accompanying models based on Approaches A and B. In particular, models based on this third approach postulate that random events occurring after the individual enters the job affect his subsequent rate of leaving the job. Initial heterogeneity may or may not be postulated, but in general heterogeneity develops with the occurrence of random events that alter the instantaneous rate at which different individuals leave the job.

Probability Laws II and IV can be derived from models based on Approach C, subtype (b), in which all stages within a job are in parallel (cf. Section 2.4). Since there are no formal differences between these models and those based on Approach B, considering these models here would be repetitious and unilluminating.

On the other hand, Probability Law V can be derived from a general model based on Approach C which postulates that holding a job is composed of two distinct stages and that movement between these two stages and eventual exit from the job is a Markov process. Figure 7.19 illustrates this model, which I have designated Model C.V.O. Stages a and b are within job j and L indicates that the individual has left job j. The instantaneous rate of transition from stage a to stage b is designated r_{ab}, and so forth. All instantaneous transition rates within the model are assumed to be finite positive constants.

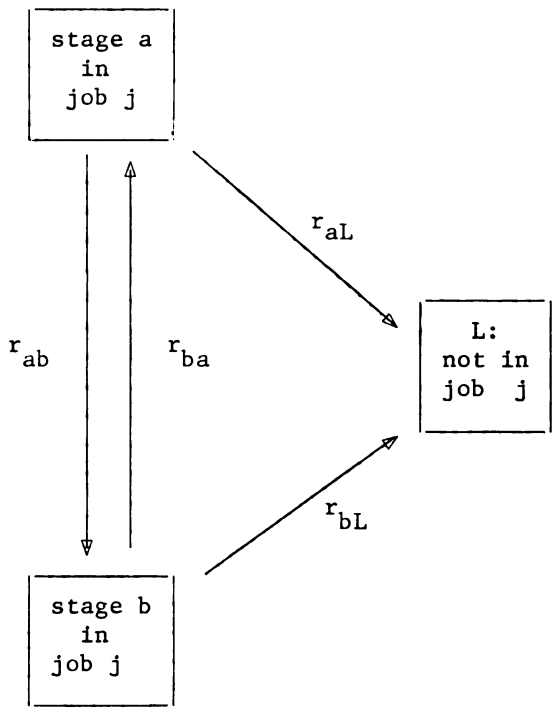

Figure 7.19 Model C.V.0, the most general two stage model of equivalent individuals in equivalent jobs j.

Let the proportion of individuals in stages a and b after duration t be represented by a(t) and b(t), respectively. Clearly

(7.12) $G_j(t) = a(t) + b(t)$

since everyone remaining in job j after duration t must be in either stage a or stage b. The model assumes that proportion Π of the individuals are initially in stage a, implying that the remaining proportion $(1 - \Pi)$ are initially in stage b, or formally stated:

(7.13) $a(0) = \Pi;$

(7.14) $b(0) = 1 - \Pi.$

Assuming that movement between stages a and b and from a or b to L is

Markovian implies that the following two equations describe the rates of change in the proportion of individuals in stages a and b:

$$\frac{da(t)}{dt} = - r_{ab}\, a(t) - r_{aL}\, a(t) + r_{ba}\, b(t); \tag{7.15}$$

$$\frac{db(t)}{dt} = r_{ab}\, a(t) - r_{ba}\, b(t) - r_{bL}\, b(t). \tag{7.16}$$

The solution to these two simultaneous differential equations, readily obtained using Laplace transforms, is

$$a(t) = \frac{(r_{ba} + \Pi r_{bL} + \Pi\lambda_1)}{(\lambda_1 - \lambda_2)} \exp[\lambda_1 t] - \frac{(r_{ba} + \Pi r_{bL} + \Pi\lambda_2)}{(\lambda_1 - \lambda_2)} \exp[\lambda_2 t] , \tag{7.17}$$

$$b(t) = \frac{(r_{ab} + (1 - \Pi) r_{aL} + (1 - \Pi)\lambda_1)}{(\lambda_1 - \lambda_2)} \exp[\lambda_1 t] - \frac{(r_{ab} + (1 - \Pi) r_{aL} + (1 - \Pi)\lambda_2)}{(\lambda_1 - \lambda_2)} \exp[\lambda_2 t] \tag{7.18}$$

where

$$\lambda_1, \lambda_2 = [(r_{aa} + r_{bb}) \pm \sqrt{(r_{aa} - r_{bb})^2 + 4 r_{ab} r_{ba}}\,]/2; \tag{7.19}$$

$$r_{aa} = - r_{ab} - r_{aL}; \tag{7.20}$$

$$r_{bb} = - r_{ba} - r_{bL}. \tag{7.21}$$

Equations (7.17) and (7.18) imply that

$$G_j(t) = \frac{(r_{ab} + r_{ba} + \Pi r_{bL} + (1 - \Pi) r_{aL} + \lambda_1)}{(\lambda_1 - \lambda_2)} \exp[\lambda_1 t] - \frac{(r_{ab} + r_{ba} + \Pi r_{bL} - (1 - \Pi) r_{aL} + \lambda_2)}{(\lambda_1 - \lambda_2)} \exp[\lambda_2 t]. \tag{7.22}$$

In spite of its structural simplicity, Model C.V.0 has some interesting features. By suitable conceptualization of stages a and b this purely mathematical model is transformed into a model with sociological substance. Let us arbitrarily identify stage a as the condition in which individuals are "strongly bound" to job j and stage b as the condition in which individuals are "weakly bound" to job j. These terms are not yet sociological concepts but simply mean that

(7.23) $$r_{bL} > r_{aL}.$$

Commitment and job satisfaction are two concepts pertaining to the binding of an individual to his job that have received considerable attention from sociologists. Strongly bound individuals could be conceptualized as committed or satisfied jobholders and weakly bound individuals as uncommitted or dissatisfied jobholders. The concepts of commitment and satisfaction are not interchangeable. An explanation of the process of individuals leaving job j in terms of commitment should imply that most persons are initially uncommitted to their job; one in terms of job satisfaction would ordinarily be expected to imply that most persons entering a job are satisfied with it. Thus the two types of explanations differ in the expected proportion of persons initially strongly bound to job j. This difference provides a basis for deciding which type of explanation fits my findings better.

Although strongly bound jobholders leave the job at a slower rate than weakly bound jobholders, Model C.V.0 assumes that both can leave job j directly, that is, without passing through any intermediary stage. The model also postulates that weakly bound jobholders may become strongly bound, and vice versa, and it implies that such changes may occur any number of times prior to an individual's inevitable exit from

job j. The assumption that movement is Markovian means that neither the length of time an individual is strongly or weakly bound to his job nor other aspects of his history within the job affect the instantaneous rates of transition from a weakly or strongly bound condition. The model generates the semblance of initial population heterogeneity through the postulate that initially equivalent individuals entering job j are randomly distributed between the two conditions. Note that this heterogeneity refers to the relationship between the individual and his job, and not to an attribute of the individual or job whose value was established before the individual ever entered the job.

Unfortunately the three independent parameters of Probability Law V (β, λ_1, λ_2) do not uniquely determine the five independent parameters of Model C.V.0 (Π, r_{ab}, r_{ba}, r_{aL}, r_{bL}). In order to calculate the parameters of the model, one must either gather information on individuals moving in and out of stages a and b or else make a priori assumptions about two parameters of the model. The former course of action is not feasible in the present research; therefore I am constrained to take the latter.

Since the number of possible choices for any of the five parameters of Model C.V.0 is infinite, the ensuing discussion centers on six special cases in which two of four parameters of the model (Π, r_{ab}, r_{ba}, r_{aL}) are assumed to take extreme values. The assumption that

(7.24) $\quad r_{bL} > r_{aL} \geq 0$

implies that

(7.25) $\quad r_{bL} > 0,$

which means that weakly bound jobholders can leave job j directly in

all cases. Table 7.8 states the special assumptions and implications of the six special cases of Model C.V.0. I have arbitrarily designated these Models C.V.1 through C.V.6. Table 7.9 reports values of the parameters of the six models for data sets Ca, Cb, and Cc.

Note that Models C.V.2 and C.V.5, both of which assume a priori that everyone is initially strongly bound to job j, i.e., that

(7.26) $\Pi = 1,$

imply necessarily that

(7.27) $\beta < 0 \text{ or } \beta > 1.$

However Table 7.5 shows that for all seventeen data sets for which Probability Law V was not reduced to Probability Law I

(7.28) $0 < \beta^* < 1.$

Thus neither Model C.V.3 nor Model C.V.5 is a possible interpretation of my findings. On the other hand, Table 7.8 indicates that Models C.V.4 and C.V.6, both of which assume a prior that everyone is initially weakly bound to job j, i.e., that

(7.29) $\Pi = 0,$

are possible interpretations of my findings because they imply that

(7.30) $0 < \beta < 1.$

Furthermore, for data sets Ca, Cb, and Cc, estimates of Π for Models C.V.1 and C.V.2 are less than 0.5 (cf. Table 7.9), which implies that most respondents were initially weakly bound to a job as nonfarm laborer. These items strongly suggest that an explanation of the process of an individual leaving a job j should be based on changes in commitment rather than on changes in job satisfaction. Therefore in the

Table 7.8 Assumptions and implications of special cases of Model C.V.0.

Model	Assumptions	Implications
C.V.1	$r_{aL} = 0$ $r_{ba} = 0$	$0 < \beta < 1$ iff $r_{bL} > r_{ab}$
C.V.2	$r_{ab} = 0$ $r_{ba} = 0$	$0 < \beta < 1$ necessarily
C.V.3	$r_{ba} = 0$ $\pi = 1$	$\beta < 0$ or $\beta > 1$ necessarily
C.V.4	$r_{ab} = 0$ $\pi = 0$	$0 < \beta < 1$ necessarily
C.V.5	$r_{aL} = 0$ $\pi = 1$	$\beta < 0$ or $\beta > 1$ necessarily
C.V.6	$r_{aL} = 0$ $\pi = 0$	$0 < \beta < 1$ necessarily

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Table 7.9 Solutions for selected two stage models of respondents leaving jobs categorized as nonfarm laborer, by educational level.[5]

Model	Data set	π	r_{ab}	r_{aL}	$(1-\pi)$	r_{ba}	r_{bL}
C.V.1	Ca	.090	.152	.000	.910	.000	.966
C.V.1	Cb	.310	.190	.000	.690	.000	.974
C.V.1	Cc	.344	.148	.000	.656	.000	.641
C.V.2	Ca	.107	.000	.152	.893	.000	.966
C.V.2	Cb	.385	.000	.190	.615	.000	.974
C.V.2	Cc	.447	.000	.148	.553	.000	.641
C.V.4	Ca	.000	.000	.152	1.000	.087	.879
C.V.4	Cb	.000	.000	.190	1.000	.302	.672
C.V.4	Cc	.000	.000	.148	1.000	.220	.421
C.V.6	Ca	.000	.167	.000	1.000	.072	.879
C.V.6	Cb	.000	.275	.000	1.000	.217	.672
C.V.6	Cc	.000	.225	.000	1.000	.143	.421
C.V.7	Ca	.000	.057	.100	1.000	.082	.879
C.V.7	Cb	.000	.138	.100	1.000	.254	.672
C.V.7	Cc	.000	.081	.100	1.000	.187	.421

[5]Underlining indicates that the value of the parameter is assumed a priori. Values of other parameters are calculated from equation (7.22) using the maximum likelihood parameter estimates for Probability Law V given in Table 7.5.

remainder of the discussion of two stage models I refer to individuals in stages a and b as committed and uncommitted jobholders, respectively.

Let us consider what effect educational level should have on the parameters of Model C.V.0 and then observe whether these predictions are supported for data sets Ca, Cb, and Cc for Models C.V.1, C.V.2, C.V.4, and C.V.6. In Section 3.3 I argued that an increase in the educational level of individuals in job j should cause an increase in (a) the level of rewards that the jobholder expects from his job, and (b) the ability of the jobholder to find more satisfactory employment.

The first relationship implies that for a given job j the initial proportion of committed jobholders Π should decrease as educational level increases. For both Models C.V.1 and C.V.2 the initial proportion of respondents committed to a job as a nonfarm laborer does, indeed, decrease as educational level increases; however, the decrease in Π is much more pronounced for the increase in years of completed schooling from 4-8 to 9-12 than from 0-3 to 4-8.

The second relationship implies that the instantaneous rate of uncommitted persons leaving job j, r_{bL}, should increase as educational level increases. Table 7.9 shows that in accordance with this prediction, the instantaneous rate of uncommitted respondents leaving a job as a nonfarm laborer increases as educational level increases for Models C.V.1, C.V.2, C.V.4, and C.V.6. A significant increase in r_{bL} accompanies each increase in educational level for the latter two models, but only with the increase from 0-3 to 4-8 years of completed schooling for the first two models.

Presumably jobholders committed to job j rarely leave to find more satisfactory employment, which suggests that educational level should

have little influence on r_{aL}. Although values of r_{aL} for nonfarm laborers obtained with Models C.V.2 and C.V.4 show a curvilinear relationship with educational level, the differences between the values are small and probably within the range of random variation. Rejection of the hypothesis that r_{aL} is independent of educational level does not seem to be indicated.

It is unclear in what way r_{ab} and r_{ba} should depend on educational level. For nonfarm laborers the estimated values of both parameters increase as years of completed schooling increases from 0-3 to 4-8 but decrease as years of completed schooling increases from 4-8 to 9-12.

The ratio r_{ba}/r_{ab} is perhaps of greater interest than the dependency of either r_{ab} or r_{ba} on educational level. This ratio measures the dynamic balance within job j between committed and uncommitted jobholders. The larger the ratio, the larger is the expected proportion of committed jobholders as duration increases. Inspection of Table 7.9 reveals that this ratio varies from zero for Model C.V.1, in which r_{ba} is assumed a priori to be zero, to infinity for Model C.V.4, in which r_{ab} is assumed a priori to be zero. In other words, without gathering information on the actual rates of movement of respondents who are uncommitted and committed, we cannot even estimate the order of magnitude of this ratio.

Table 7.9 includes estimates of parameters for Model C.V.7, a seventh special case of Model C.V.0 that differs from Model C.V.6 only in assuming that r_{aL} is the reasonable but arbitrarily chosen figure of 0.1 rather than zero. For Model C.V.7 the ratio r_{ba}/r_{ab} decreases as educational level increases, which implies that the tendency for jobholders to become committed as duration increases declines as

educational level rises. While this is consistent with other predictions on the effect of educational level on the process of leaving a given job j, empirical grounds for preferring Model C.V.7 over C.V.1, C.V.2, C.V.4, and C.V.6 are not available.

In actuality the special assumptions of all special cases of Model C.V.0 seem unrealistic, some more so than others. Although all cases considered indicate that most respondents are initially uncommitted to a job as a nonfarm laborer, it is unlikely that everyone is initially uncommitted, as Models C.V.4, C.V.6, and C.V.7 assume. And even though committed persons would not be expected to leave the job because of an active interest in finding another job, events unrelated to this (illness, family crises, etc.) occur sufficiently often that r_{aL} cannot be exactly zero as Models C.V.1 and C.V.6 postulate. Finally, the assumption that uncommitted persons never become committed, as in Models C.V.1 and C.V.2, and the corresponding assumption that committed persons never become uncommitted, as in Models C.V.2 and C.V.4, implies a degree of stability in an individual's evaluation of his job contrary to casual observation.

This discussion has shown that Model C.V.0 is a reasonable basis for a substantive explanation of the process of equivalent individuals leaving equivalent jobs. If future evidence should indicate that the instantaneous rate of equivalent individuals leaving equivalent jobs does increase with initial increases in duration before eventually declining with further increases in duration, as a few previous reports have suggested, then Model C.V.0 can readily be extended to an analogous three stage model leading to a version of Probability Law VI that possesses this property.

Meanwhile there is an obvious need for a careful conceptualization and operationalization of the two stages of Model C.V.O and for measurement of movement in and out of these stages of a job. This research should be coupled with additional theoretical development and empirical investigation concerning the identification of equivalent individuals in equivalent jobs. Further proliferation of probability laws that are derived from purely mathematical models is not needed to obtain satisfactory predictions of observed rates of movement of equivalent individuals from equivalent jobs and, more importantly, will not deepen our understanding of the mobility process.

CHAPTER 8

The Process of Individuals Entering a New Social Position: The Identification of Equivalent Respondents and Equivalent Jobs

This chapter contains a report and discussion of my findings pertaining to the process of respondents entering a new job. I consider the following specific topics: (1) the equivalence of crude vacancy rates of different occupations in a given geographical location, (2) the identification of equivalent destinations, (3) the identification of equivalent origins, (4) the identification of equivalent individuals, (5) the correspondence between the theoretical construct time t and observable measures of time, and (6) the validity of the Markov assumption.

8.1 The equivalence of crude vacancy rates of different occupations in a given geographical location

In Section 4.2 I postulated that $q_{x_j y_j x_k | y_k}(t)$, the conditional probability of entering a job in occupation y_k, given that the individual moves to location x_k from occupation y_j in location x_j, is proportional to the fraction of vacancies in location x_k which occur in occupation y_k:

$$(8.1) \qquad q_{x_j y_j x_k | y_k}(t) = \alpha_{x_j y_j x_k | y_k}(t)\, v_{x_k y_k}(t)\, v_{x_k y.}(t),$$

where $\alpha_{x_j y_j x_k | y_k}(t)$ is the attraction of occupation y_k, given that the individual moves to location x_k from occupation y_j in location x_j;

$v_{x_k y_k}(t)$ is the number of vacancies in occupation y_k and location x_k; and . indicates summation over the missing index. I also demonstrated that if $0_{x_k y_k}(t)$, the crude vacancy rate of occupation y_k in location x_k, is the same for every occupation in that location at a given time t, then

$$(8.2) \qquad \alpha_{x_j y_j x_k | y_k}(t) = q_{x_j y_j x_k | y_k}(t)\, n_{x_k y.}(t)/n_{x_k y_k}(t),$$

where $n_{x_k y_k}(t)$ is the number of filled positions in occupation y_k and location x_k. Equation (8.2) is used to study the equivalence of different destinations in Section 8.2 and the equivalence of different points in calendar time in Section 8.5.

Comparing values of $0_{x_k y_k}(t)$ for different occupations in a given geographical location permits one to assess the validity of equation (8.2) and therefore to determine how much confidence can be placed in conclusions based on this equation. Although values of $0_{x_k y_k}(t)$ can not be obtained directly in this study, I showed in Section 4.2 that they can be estimated from the expected density of leavers from occupation y_k in location x_k after duration u, $\bar{f}_{x_k y_k}(u)$, and the growth rate of occupation y_k in location x_k, $g_{x_k y_k}(t)/n_{x_k y_k}(t)$, if the following assumptions are valid: (1) individuals entering and leaving positions in occupation y_k and location x_k belong to a homogeneous population; (2) every position in occupation y_k and location x_k is filled at the same moment that the position is vacated or created; (3) the instantaneous rate of leaving (x_k, y_k) depends on duration u but not on calendar time or on the jobholder's age.

The first assumption is the most troublesome. The findings presented in Section 6.2b indicate that respondents in a given occupation

y_k and location x_k varied on attributes affecting the rate of leaving the job. More particularly, in many cases an individual entering a given job probably differs significantly from his predecessor in attributes that influence the rate of leaving the job. Since the formulation given in Section 4.2 for determining crude vacancy rates only applies to a set of equivalent jobs occupied by equivalent individuals, only the crude vacancy rates associated with the twenty-one data sets described in Table 7.1 can be estimated for a given location x_k in the present study. Since the respondents represent a very small fraction of the persons in occupation y_k and location x_k, the crude vacancy rates associated with the data sets corresponding to y_k and x_k do not determine, but merely suggest, the value of $0_{x_k y_k}(t)$.

Although the second assumption is certainly not exactly true in most instances, the length of time that positions are unfilled is probably sufficiently short to be neglected without serious error. The third assumption also appears reasonable. My findings show that during the period 1935-1967 the instantaneous rate of equivalent respondents leaving equivalent jobs was relatively independent of calendar time and of the respondent's age (cf. Section 6.2c), but in most cases did depend on duration (cf. Section 7.1). Furthermore, the findings reported in Sections 7.2 through 7.4 indicate that Probability Laws II, IV, or V adequately describe the process of equivalent respondents leaving equivalent jobs for the seventeen data sets in which the instantaneous rate of leaving the job noticeably depended on duration, and that Probability Law I is satisfactory for the four other data sets. The maximum likelihood estimates of parameters for these probability laws (cf. Tables 7.2 through 7.5) permit us to write an explicit, adequate

formulation for the expected density of leavers after duration u for each of the twenty-one data sets.

Thus estimating values of the crude vacancy rates associated with the twenty-one data sets seems both reasonable and possible if the growth rates of the groups represented by the data sets can be estimated. For the purpose of this discussion I assume that the growth rate, $g_{x_k y_k}(t)/n_{x_k y_k}(t)$, is a constant γ. This implies that

$$(8.3) \qquad b_{x_k y_k}(t) = n_{x_k y_k}(0) \exp[\gamma t]$$

or

$$(8.4) \qquad \ln n_{x_k y_k}(t) = \gamma t + \ln n_{x_k y_k}(0).$$

Even though these equations ignore short-term cyclical fluctuations and cannot be true over very long periods of time, they should give a satisfactory approximation of γ for the thirty-three year period examined in this research. If values of $n_{x_k y_k}(t)$ are known for two or more points in time, then γ can be easily estimated from equation (8.4) by the method of least squares.

Information in the 1960 Census of Population of the U.S. Bureau of the Census on numbers of employed males in various occupational categories in Michigan and in Texas for the years 1940, 1950, and 1960 (cf. Table 5.4) provides one possible source of information on $n_{x_k y_k}(t)$. Using this information to estimate γ has several disadvantages, the most important being that the census probably lumps together groups with different growth rates for the occupation in question. Thus the growth rate of the total population in a particular occupational category and location may differ greatly from that of any particular

subgroup being considered, e.g., Mexican-American men with a given educational level. A secondary disadvantage is that the number of persons in each occupation is known for only three points in time.

Estimates of $n_{x_k y_k}(t)$ can also be obtained by taking retrospective censuses on the respondents' work histories. Using this information to estimate γ also has disadvantages, the primary one being that in using such censuses one implicitly assumes that the number of respondents in a particular category at a given time is representative of the actual number of persons in that category at that time. But clearly the number of respondents in a particular category increasingly underrepresents the actual number in that category as the censuses are projected back in calendar time. In general this leads to an apparent growth rate greater than would be found from a series of true censuses. Similarly the gradual migration of many respondents from Texas to Michigan during 1935-1967 distorts the growth rate of any particular category in these locations, decreasing it for Texas and increasing it for Michigan.

Another disadvantage of using retrospective censuses of the respondents' histories to estimate $n_{x_k y_k}(t)$ is that the comparatively small number of respondents in this study introduces considerable random variation into the estimated numbers in a particular category at a given time. To some extent increasing the frequency of these censuses reduces the error in γ resulting from such random fluctuations.

While neither of the above sources of information on $n_{x_k y_k}(t)$ can be considered ideal, together they give some indication of the order of magnitude of γ for different groups of equivalent individuals in equivalent jobs. Table 8.1 reports estimates of γ for the twenty-one data

Table 8.1 Estimates of the rate of growth of sets of equivalent individuals in equivalent jobs.

Data set	Michigan		Texas	
	γ_c	γ_r	γ_c	γ_r
Aa	-.049	-	-	-
Ab	-.049	-.010	-	-
Ac	-.049	.011	-	-
Ba	-	-	-.036	-.009
Bb	-	-	-.036	-.001
Ca	-.006	.097	.012	-
Cb	-.006	.090	.012	-.003
Cc	-.006	.065	.012	-.021
Da	-.049	-	-.036	-
Db	-.049	.040	-.036	-.006
Dc	-.049	.054	-.036	-.017
Ea	.014	.108	-	-
Eb	.014	.096	-	-
Ec	.014	.137	-	-
Ed	.014	.094	-	-
Ee	.014	.059	-	-
Fa	.014	.095	-	-
Fb	.014	.109	-	-
Fc	.014	.109	-	-
Fd	.014	.158	-	-
Fe	.014	.098	-	-

sets in Michigan and in Texas obtained by using the method of least squares with equation (8.4) on estimates of $n_{x_k y_k}(t)$ from the two sources. I have designated the estimate of γ based on information in the 1960 Census of Population γ_c and that based on retrospective censuses of the respondents' histories γ_r. Values of $n_{x_k y_k}(t)$ in the latter were estimated as the mean number of respondents in each data set in each location for each year examined (1945-1967 for operatives, 1935-1967 for all other occupations). Since $\ln 0$ is $-\infty$, any estimate of $n_{x_k y_k}(t)$ identically zero was disregarded in calculating γ_r. Estimates of γ_r are omitted for those data sets for which the mean number of respondents in each year averaged less than one.

If the growth rate of a group of equivalent individuals occupying equivalent jobs is a constant γ, and if the expected density of leavers after duration u is $\kappa \exp[\kappa u]$, which means that Probability Law I describes the process of an individual leaving a job, then the crude vacancy rate $O(t)$ is $\kappa + \gamma$. Table 8.2 exhibits the crude vacancy rates associated with the twenty-one data sets in Michigan and in Texas under these assumptions.

Comparisons between Michigan and Texas are possible for only a few data sets; however, in these cases the crude vacancy rate associated with a particular data set differs only slightly between Michigan and Texas, whichever estimate of γ is used. On the other hand, for a given location the crude vacancy rates vary considerably with attributes of individuals, and even more with occupational category. Although the estimates in Table 8.2 are very rough, the extent of variation in the crude vacancy rates for a given location appears too large to be attributed entirely to errors in estimating γ or to the

Table 8.2 Estimates of crude vacancy rates assuming Probability Law I describes the process of leaving a job.

	Michigan			Texas	
Data set	$O(\gamma=0)$	$O(\gamma_c)$	$O(\gamma_r)$	$O(\gamma_c)$	$O(\gamma_r)$
Aa	1.787	1.738	-	-	-
Ab	.967	.918	.957	-	-
Ac	.596	.547	.607	-	-
Ba	.527	-	-	.491	.518
Bb	.239	-	-	.203	.238
Ca	.694	.688	.791	.706	-
Cb	.395	.389	.485	.407	.392
Cc	.269	.263	.334	.281	.248
Da	.437	.388	-	.401	-
Db	.299	.250	.339	.263	.293
Dc	.203	.154	.257	.167	.186
Ea	.563	.577	.671	-	-
Eb	.134	.148	.230	-	-
Ec	.201	.215	.338	-	-
Ed	.088	.102	.182	-	-
Ee	.095	.109	.154	-	-
Fa	.176	.190	.271	-	-
Fb	.083	.097	.192	-	-
Fc	.090	.104	.199	-	-
Fd	.082	.096	.240	-	-
Fe	.044	.058	.142	-	-

inadequacy of Probability Law I in describing the process of an individual leaving a job.

Better estimates of the crude vacancy rates are obtained by assuming that the expected density of leavers after duration u is $\beta\lambda_1 \exp[-\lambda_1 u] + (1-\beta)\lambda_2 \exp[-\lambda_2 u]$, i.e., that Probability Law V describes the process of an individual leaving a job. In this case, if the growth rate is again a constant γ and time t is large, then the crude vacancy rate $O(t)$ equals $1/\mu + \gamma + a\gamma/(b+\gamma)$, where b, μ, and a are given by equations (4.31), (4.32), and (4.33), respectively. Table 8.3 displays the crude vacancy rates associated with the twenty-one data sets in Michigan and in Texas under these assumptions.

Although Probability Law V described the process of equivalent respondents leaving equivalent jobs much better than Probability Law I for seventeen of the twenty-one data sets (cf. Section 7.4), the crude vacancy rates associated with a data set in a given location vary only slightly with the probability law postulated according to a comparison of Tables 8.2 and 8.3. The crude vacancy rates associated with data sets Ab and Ac assuming the growth rate is γ_c are exceptions to this. But on the whole, comments on Table 8.2 apply equally well to Table 8.3: the crude vacancy rates associated with a particular data set in Michigan and in Texas differ little, but the extent of variation in the crude vacancy rates for a given location with attributes of individuals, and especially with occupational category, is substantial and much too great to be explained entirely by errors in estimating γ or by the inadequacy of Probability Law V in describing the process of an individual leaving a job. Although inconclusive, this evidence suggests that equation (8.2) is at best a rough approximation to equation (8.1),

Table 8.3 Estimates of crude vacancy rates assuming Probability Law V describes the process of leaving a job.

Data set	Michigan			Texas	
	$O(\gamma=0)$	$O(\gamma_c)$	$O(\gamma_r)$	$O(\gamma_c)$	$O(\gamma_r)$
Aa	1.785	1.678	-	-	-
Ab	.967	.599	.947	-	-
Ac	.549	.331	.589	-	-
Ba	.527	-	-	.459	.510
Bb	.238	-	-	.195	.237
Ca	.614	.601	.788	.639	-
Cb	.376	.366	.512	.395	.371
Cc	.258	.249	.347	.275	.227
Da	.415	.344	-	.363	-
Db	.298	.247	.339	.260	.292
Dc	-	-	-	-	-
Ea	-	-	-	-	-
Eb	.096	.119	.249	-	-
Ec	.160	.180	.346	-	-
Ed	.042	.067	.197	-	-
Ee	-	-	-	-	-
Fa	.053	.089	.266	-	-
Fb	.029	.053	.199	-	-
Fc	-	-	-	-	-
Fd	-	-	-	-	-
Fe	.039	.054	.145	-	-

even though it cannot be evaded in examining certain issues in the remainder of this chapter.

8.2 Findings concerning the identification of equivalent destinations

Table 8.4 reports the observed proportion of intra-Michigan transitions to eight occupational categories by previous occupation for the years 1945-1954 and 1955-1967. Table 8.5 gives the corresponding estimates of the attraction of these transitions, $\alpha_{x_j y_j x_k | y_k}(t)$, which were calculated from equation (8.2) under the supposition that the proportions in Table 8.4 are estimates of $q_{x_j y_j x_k | y_k}(t)$ and that the numbers in Table 5.4 are estimates of $n_{x_k y_k}(t)$. Because of the dubious validity of equation (8.2), estimates of $\alpha_{x_j y_j x_k | y_k}(t)$ and their interpretation in this chapter are very tentative.

As I explained in Section 4.3, one cannot decide whether different types of jobs are equivalent destinations by directly comparing proportions of transitions to the destinations because differences in the number of vacancies can mask the sociological similarities and differences of different destinations. Consequently one can only study the equivalence of different destinations by comparing their attraction for individuals with the same origin (x_j, y_j).

For example, Table 8.4 shows that during 1945-1954 and 1955-1967 the proportion of intra-Michigan transitions from operative to white collar worker was relatively similar to the proportion of intra-Michigan transitions from operative to farm laborer. However, Table 8.5 indicates that during 1945-1954 and 1955-1967 an intra-Michigan transition from operative to farm laborer attracted, respectively, seventeen and twenty-six times as many respondents as an intra-Michigan transition from operative to white collar worker. Thus a

Table 8.4 Proportion of intra-Michigan transitions to eight occupational categories by previous occupation and by year.

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	1945-1954	1955-1967	1945-1954	1955-1967	1945-1954	1955-1967
White collar workers	.029	.049	.016	.013	.012	.026
Craftsmen & foremen	.081	.163	.048	.084	.024	.038
Drivers & deliverymen	.029	.028	.048	.026	.036	.077
Operatives	.669	.535	.524	.422	.595	.462
Service workers	.029	.066	.079	.058	.024	.090
Nonfarm laborers	.128	.118	.238	.312	.155	.231
Farm proprietors	.000	.000	.000	.000	.012	.013
Farm laborers	.035	.042	.048	.084	.143	.064
TOTAL PROPORTION DOWN	1.000	1.001	1.001	0.999	1.001	1.001
TOTAL N	172	288	63	154	84	78

Table 8.5 Attraction of intra-Michigan transitions to eight occupational categories by previous occupation and by year.

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	1945-1954	1955-1967	1945-1954	1955-1967	1945-1954	1955-1967
White collar workers	.10	.14	.05	.04	.04	.08
Craftsmen & foremen	.37	.72	.22	.37	.11	.17
Drivers & deliverymen	.63	.54	1.0	.50	.78	1.5
Operatives	2.8	2.4	2.2	1.9	2.5	2.1
Service workers	.51	1.1	1.4	.97	.42	1.5
Nonfarm laborers	2.0	2.1	3.7	5.4	2.4	4.0
Farm proprietors	0.0	0.0	0.0	0.0	.19	.41
Farm laborers	1.7	3.7	2.4	7.4	7.1	5.6
TOTAL N	172	288	63	154	84	78

comparison of the attraction of white collar work and farm labor as occupational destinations suggests a great difference between these occupations that a comparison of the proportion of transitions to these occupational destinations does not reveal.

Table 8.5 implies that the respondents entered jobs as operatives, nonfarm laborers, and farm laborers much more frequently than random sampling of occupational destinations predicts, and entered jobs as white collar workers, craftsmen and foremen, and farm proprietors markedly less often than random sampling predicts. If, as seems reasonable, the respondents generally prefer jobs as white collar workers, craftsmen and foremen, and farm proprietors to jobs as operatives, nonfarm laborers, and farm laborers, then this suggests that the respondents found jobs in the former occupations less attainable than jobs in the latter occupation.[1] Presumably this occurred because employers filling vacancies in the former occupations, but not the latter, were able to hire individuals with better qualifications than the respondents'.[2] Such conclusions should be buttressed with independently-gathered information on the respondents' preference ordering of jobs in different occupations and on employers' preference ordering for filling vacancies in different occupations with individuals with particular characteristics.

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[1]The extremely low attraction of a job as a farm proprietor may partially result from the number of individuals employed as farm proprietors (cf. Table 5.4) overestimating the number of vacancies in this occupation. The sharp decline in farm proprietors during the period examined (cf. Table 5.4) and the high mean tenure for this occupation (cf. Table 5.1) lend plausibility to this hypothesis.

[2]This statement does not apply to self-employed farm proprietors.

Table 8.5 shows that the attraction of jobs as service workers and of jobs as drivers and deliverymen falls within the range 0.5 to 1.5, which means that respondents entered these occupations in proportions fairly close to what random sampling predicts. In most cases jobs in these two occupations attracted the respondents more than jobs as white collar workers, craftsmen and foremen, and farm proprietors but less than jobs as operatives, nonfarm laborers, and farm laborers. Because the respondents probably prefer jobs as white collar workers, craftsmen and foremen, and farm proprietors to jobs as service workers and drivers and deliverymen, the respondents apparently secured jobs in the latter occupations more easily than jobs in the former occupations. On the other hand, variability in the rewards (money, prestige, etc.) associated with jobs as service workers and as drivers and deliverymen makes it unclear why jobs in these occupations attracted the respondents less than jobs as operatives, nonfarm laborers, and farm laborers. Again, one needs information on preferences of the respondents and of employers in order to clarify the reasons for the relative magnitude of the attraction of different occupational destinations.

Because of the comparatively small number of transitions which form the data for this analysis, only four occupational categories are used in the remainder of this chapter: operative, nonfarm laborer, farm laborer, and other occupations. I have collapsed jobs as white collar workers, craftsmen and foremen, farm proprietors, service workers, and drivers and deliverymen into the single category other occupations in order to avoid having an unreasonably small number of observations for any cell of a table. However, Table 8.5 does not suggest that jobs in these five occupational categories were equivalent

destinations for the respondents.

Table 8.6 reports the proportion of intrastate transitions to four occupational categories by year, previous occupation, and location. The corresponding estimates of the attraction of these transitions are given in Table 8.7.

A comparison of Tables 8.6 and 8.7 indicates that differences in the observed proportions of intrastate transitions among occupations for Michigan and Texas can be attributed, to a considerable extent, to differences in the distribution of vacancies in the two locations. For example, the proportions of intrastate transitions from nonfarm laborer to operative for 1945-1954 and 1955-1967 are, respectively, 3.3 and 3.7 times greater in Michigan than in Texas. However the attractions of this transition are, respectively, only 1.6 and 2.1 times greater in Michigan than in Texas. Similarly, the proportions of intrastate transitions from nonfarm laborer to farm laborer for 1945-1954 and 1955-1967 are, respectively, 7.1 and 6.8 times greater in Texas than in Michigan. But the attractions of this transition are, respectively, only 1.9 and 1.7 times greater in Texas than in Michigan.

Comparison of the attractions of intrastate transitions between occupations for the two locations (cf. Table 8.7) implies that differences in job opportunities for respondents in the two locations were not extremely large aside from what is attributable to differences in vacancies. In only five of the eighteen possible comparisons for the two locations is the attraction of an intrastate transition more than two times greater in one location than in the other, and in only one more than three times greater. This suggests that neither the desirability of occupations to respondents nor the desirability of

Table 8.6 Proportion of intrastate transitions to four occupational categories by year, previous occupation, and geographical location.

1945-1954

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	Texas	Mich.	Texas	Mich.	Texas	Mich.
Operative	.500	.669	.160	.524	.143	.595
Nonfarm laborer	.125	.128	.240	.238	.268	.155
Farm laborer	.250	.035	.400	.048	.321	.143
Other occupations	.125	.169	.200	.190	.268	.107
TOTAL PROPORTION DOWN	1.000	1.001	1.000	1.000	1.000	1.000
TOTAL N	24	172	25	63	56	84

1955-1967

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	Texas	Mich.	Texas	Mich.	Texas	Mich.
Operative	.524	.535	.115	.422	.323	.462
Nonfarm laborer	.048	.118	.154	.312	.419	.231
Farm laborer	.286	.042	.423	.084	.129	.064
Other occupations	.143	.306	.308	.182	.129	.244
TOTAL PROPORTION DOWN	1.001	1.001	1.000	1.000	1.000	1.001
TOTAL N	21	288	26	154	31	78

Table 8.7 Attraction of intrastate transitions to four occupational categories by year, previous occupation, and geographical location.

1945-1954

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	Texas	Mich.	Texas	Mich.	Texas	Mich.
Operative	4.3	2.8	1.4	2.2	1.2	2.5
Nonfarm laborer	1.3	2.0	2.6	3.7	2.9	2.4
Farm laborer	3.3	1.7	5.3	2.4	4.3	7.1
TOTAL N	24	172	25	63	56	84

1955-1967

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	Texas	Mich.	Texas	Mich.	Texas	Mich.
Operative	4.1	2.4	.90	1.9	2.5	2.1
Nonfarm laborer	.59	2.1	1.9	5.4	5.2	4.0
Farm laborer	6.1	3.7	9.1	7.4	2.8	5.6
TOTAL N	21	288	26	154	31	78

respondents as potential employees changed radically with location.

Nevertheless, differences between the two locations in the attraction of intrastate transitions to particular occupations do not seem either random or negligible. In particular, note that for both time intervals a job as a farm laborer attracted respondents leaving a job as an operative or nonfarm laborer less in Michigan than in Texas, but attracted those leaving a job as a farm laborer more in Michigan than in Texas. This suggests that respondents leaving a job as an operative or nonfarm laborer found jobs in these same occupations more attainable in Michigan than in Texas, but that those leaving a job as a farm laborer found jobs as an operative or nonfarm laborer less attainable in Michigan than in Texas. In other words, respondents apparently found the social boundary between jobs as operatives and nonfarm laborers and jobs as farm laborers more impervious in Michigan than in Texas.

Table 8.8 shows the proportion of transitions from Texas to four occupational categories by year, previous occupation, and location of destination; Table 8.9 gives the corresponding estimates of the attraction of these transitions.

Table 8.9 is of much greater interest than Table 8.8 in assessing the effect of out-migration on a transition between particular occupations because the proportion of transitions between occupations depends on the vacancy structure in the location entered. The most notable feature of Table 8.9 is the much stronger attraction of a job as a farm laborer for respondents who migrated to Michigan rather than remained in Texas. Because migratory farm labor has served as an important vehicle for conveying Mexican-Americans in Texas to the

Table 8.8 Proportion of transitions from Texas to four occupational categories by year, previous occupation, and geographical location of destination.

1945-1954

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	Texas	Mich.	Texas	Mich.	Texas	Mich.
Operative	.500	.520	.160	.222	.143	.314
Nonfarm laborer	.125	.120	.240	.037	.268	.143
Farm laborer	.250	.240	.400	.630	.321	.400
Other occupations	.125	.120	.200	.111	.268	.143
TOTAL PROPORTION DOWN	1.000	1.000	1.000	1.000	1.000	1.000
TOTAL N	24	25	25	27	56	35

1955-1967

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	Texas	Mich.	Texas	Mich.	Texas	Mich.
Operative	.524	.350	.115	.188	.323	.268
Nonfarm laborer	.048	.250	.154	.312	.419	.244
Farm laborer	.286	.200	.423	.438	.129	.390
Other occupations	.143	.200	.308	.062	.129	.098
TOTAL PROPORTION DOWN	1.001	1.000	1.000	1.000	1.000	1.000
TOTAL N	21	20	26	16	31	41

Table 8.9 Attraction of transitions from Texas to four occupational categories by year, previous occupation, and geographical location of destination.

1945-1954

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	Texas	Mich.	Texas	Mich.	Texas	Mich.
Operative	4.3	2.1	1.4	.91	1.2	1.3
Nonfarm laborer	1.3	1.9	2.6	.58	2.9	2.2
Farm laborer	3.3	12.	5.3	31.	4.3	20.
TOTAL N	24	25	25	27	56	35

1955-1967

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	Texas	Mich.	Texas	Mich.	Texas	Mich.
Operative	4.1	1.6	.90	.86	2.5	1.2
Nonfarm laborer	.59	4.3	1.9	5.4	5.2	4.2
Farm laborer	6.1	18.	9.1	38.	2.8	34.
TOTAL N	21	20	26	16	31	41

Michigan labor market, this finding is not surprising.

8.3 Findings concerning the identification of equivalent origins

In this section I report and discuss findings concerning the effect of origins in different locations, occupations, and industries on transitions to a destination in a particular occupation and location. Since the destinations are identical, any differences in the proportion of transitions to a particular occupation must be attributed to the attraction of the occupation varying with some attribute of the origin. Consequently, if the attraction of different occupational destinations depends on an attribute of the origin, then the value of χ^2 computed for the corresponding contingency table should be greater than expected from random variation.

Table 8.10 reports the proportion of transitions to four occupational categories in Michigan by previous location for respondents leaving jobs in three occupations during 1945-1954 and 1955-1967. Since $\chi^2_{.01,3} = 11.3$ and the calculated values of χ^2 for the six subtables of Table 8.10 are all greater than 11.3, it seems clear that the attraction of different occupations in Michigan for the respondents, and concomitantly the conditional probability of a transition to a particular occupation in Michigan, did depend on the geographical origin of the individual.

In particular, Table 8.10 shows that respondents originating in Texas rather than in Michigan are from three to thirteen times more likely to enter a job in Michigan as a farm laborer. Coupled with the finding in the previous section on the effect of out-migration on the attraction of respondents to a job as a farm laborer, this indicates that migrants from Texas to Michigan are much more strongly attracted

Table 8.10 Proportion of transitions to four occupational categories in Michigan by year, previous occupation, and previous location.

1945-1954

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	Texas	Mich.	Texas	Mich.	Texas	Mich.
Operative	.520	.669	.222	.524	.314	.595
Nonfarm laborer	.120	.128	.037	.238	.143	.155
Farm laborer	.240	.035	.630	.048	.400	.143
Other occupations	.120	.169	.111	.190	.143	.107
TOTAL PROPORTION DOWN	1.000	1.001	1.000	1.000	1.000	1.000
TOTAL N	25	172	27	63	35	84
χ^2, 3 d.f.	16.1		37.8		11.6	

1955-1967

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	Texas	Mich.	Texas	Mich.	Texas	Mich.
Operative	.350	.535	.188	.422	.268	.462
Nonfarm laborer	.250	.118	.312	.312	.244	.231
Farm laborer	.200	.042	.438	.084	.390	.064
Other occupations	.200	.306	.062	.182	.098	.244
TOTAL PROPORTION DOWN	1.000	1.001	1.000	1.000	1.000	1.001
TOTAL N	20	288	16	154	41	78
χ^2, 3 d.f.	13.5		18.6		21.7	

to farm labor than nonmigrants in either the location left or the location entered. This accords with my argument in Section 4.3 that migrants are more attracted to the least desirable jobs than nonmigrants. Since migration was voluntary, residence in Michigan apparently compensated the respondents in some way for a less favorable position in the labor market.

Table 8.11 gives the proportion of intrastate transition to four occupational categories by previous occupation for respondents in Michigan and in Texas during 1935-1944, 1945-1954, and 1955-1967. Since $\chi^2_{.05,6} = 12.6$ and since the computed values of χ^2 are greater than this for both locations in 1945-1954 and in 1955-1967, the attraction of different occupations does not seem independent of the respondent's previous occupation during these years. Although the calculated χ^2 values are slightly less than 12.6 for both locations in 1935-1944, occupational origin still has a noticeable effect on the occupational destination. Note that for all three time intervals in Michigan, a transition to a particular occupation is, with one exception, more likely if the previous occupation was in the same category. This supports my prediction in Section 4.3. However, this pattern is not particularly obvious in Texas.

Table 8.12 contains the proportion of intra-Michigan transitions during 1945-1967 to four occupational categories by previous industry for respondents leaving jobs as nonfarm laborers and as operatives. The influence of industrial classification for those leaving jobs as nonfarm laborers was, as expected, extremely slight: the observed value of χ^2 is so small that random variation can be expected to produce a larger value more than three-fourths of the time. On the other hand,

Table 8.11 Proportion of intrastate transitions to four occupational categories by geographical location, year, and previous occupation.

intra-Michigan transitions

Occupational Destination	1935-1944 Previous occupn: Oper.	Nf.L.	F.L.	1945-1954 Previous occupn: Oper.	Nf.L.	F.L.	1955-1967 Previous occupn: Oper.	Nf.L.	F.L.
Operative	.641	.519	.568	.669	.524	.595	.535	.422	.462
Nonfarm laborer	.128	.222	.162	.128	.238	.155	.118	.312	.231
Farm laborer	.051	.000	.189	.035	.048	.143	.042	.084	.064
Other occupations	.179	.259	.081	.169	.190	.107	.306	.182	.244
TOTAL PROPORTION DOWN	0.999	1.000	1.000	1.001	1.000	1.000	1.001	1.000	1.001
TOTAL N	39	27	37	172	63	84	288	154	78
χ^2, 6 d.f.		11.7			17.6			32.3	

intra-Texas transitions

Occupational Destination	1935-1944 Previous occupn: Oper.	Nf.L.	F.L.	1945-1954 Previous occupn: Oper.	Nf.L.	F.L.	1955-1967 Previous occupn: Oper.	Nf.L.	F.L.
Operative	.158	.038	.169	.500	.160	.143	.524	.115	.323
Nonfarm laborer	.316	.500	.308	.125	.240	.268	.048	.154	.419
Farm laborer	.105	.269	.354	.250	.400	.321	.286	.423	.129
Other occupations	.421	.192	.169	.125	.200	.268	.143	.308	.129
TOTAL PROPORTION DOWN	1.000	0.999	1.000	1.000	1.000	1.000	1.001	1.001	1.000
TOTAL N	19	26	65	24	25	56	21	26	31
χ^2, 6 d.f.		12.0			14.0			22.1	

Table 8.12 Proportion of intra-Michigan transitions to four occupational categories by previous occupation and by previous industry, 1945-1967.

Occupational Destination	Previous occupn: Operative				Previous occupn: Nonfarm laborer	
	Previous industry:				Previous industry:	
	Fabr. Met.	Motor Veh.	Food Prod.	Other	Constr.	Other
Operative	.620	.526	.632	.580	.440	.465
Nonfarm laborer	.088	.129	.105	.153	.319	.257
Farm laborer	.051	.017	.105	.020	.069	.079
Other occupations	.241	.328	.158	.247	.172	.198
TOTAL PROPORTION DOWN	1.000	1.000	1.000	1.000	1.000	0.999
TOTAL N	137	116	57	150	116	101
χ^2		18.3 (9 d.f.)			1.1 (3 d.f.)	

the effect of the industrial origin of operatives on their occupational destination cannot be dismissed as readily. Random variation should give a value of χ^2 as large as that calculated for this subtable only three times out of one hundred. However, a close inspection of this subtable reveals that one cell contributes an unusually large amount to the total χ^2 value. If the contribution of this cell is omitted, the computed value of χ^2 is 11.9; a value this large can be expected about one-fifth of the time in a random sample. Since this cell, which shows the proportion of transitions from an operative in food manufacturing to farm laborer, has an expected cell frequency of 2.2, well below the value of five customarily desired, one can not rule out the hypothesis that occupational destination of respondents leaving a job as an operative was independent of the industry left.

8.4 Findings concerning the identification of equivalent individuals

Table 8.13 presents the proportion of intra-Michigan transitions during 1945-1967 to four occupational categories by educational level of the respondent for those leaving a job as an operative, nonfarm laborer, or farm laborer. As $\chi^2_{.05,6} = 12.6$ and the observed value of χ^2 is larger than this for the subtables on all three previous occupations, the attraction of an occupational destination for a respondent does appear to depend on his educational level.

In Section 4.4 I predicted that as their educational level rose, men would be more likely to enter the more desirable jobs and less likely to enter the less desirable jobs. But an examination of the variation in the proportion of transition to a particular occupation with increasing educational level does not reveal any consistent trends for respondents leaving different occupations. For instance, as

Table 8.13 Proportion of intra-Michigan transitions to four occupational categories by previous occupation and by educational level, 1945-1967.

Occupational Destination	Previous occupn: Operative			Previous occupn: Nonfarm laborer			Previous occupn: Farm laborer		
	Years Compl. Schooling			Years Compl. Schooling			Years Compl. Schooling		
	0-3	4-8	9-12	0-3	4-8	9-12	0-3	4-8	9-12
Operative	.579	.626	.544	.531	.329	.530	.638	.541	.390
Nonfarm laborer	.187	.100	.105	.327	.353	.205	.106	.189	.293
Farm laborer	.065	.027	.035	.041	.071	.096	.149	.122	.024
Other occupations	.168	.247	.316	.102	.247	.169	.106	.149	.293
TOTAL PROPORTION DOWN	0.999	1.000	1.000	1.001	1.000	1.000	0.999	1.001	1.000
TOTAL N	107	182	171	49	85	83	47	74	41
χ^2, 6 d.f.		14.2			13.1			15.0	

educational level increases, the attraction of a job as farm laborer decreases for respondents leaving a job as farm laborer, increases for those leaving a job as nonfarm laborer, and decreases and then increases for those leaving a job as an operative. Thus, the effect of educational level on the attraction of a particular occupational destination is not always monotonic and, more importantly, depends on the previous occupation.

Table 8.14 exhibits the proportion of intra-Michigan transitions during 1945-1967 to four occupational categories by the location in which the respondent was reared for those leaving a job as an operative, nonfarm laborer, or farm laborer. Since $\chi^2_{.05,3} = 7.8$ and the calculated values of χ^2 are less than this for all three subtables of Table 8.14, occupational classification of the job entered appears independent of the location in which the respondent was reared. This is not unusual, as I expected both the location reared and migrant farm background to influence occupational destination decidedly less than the respondent's educational level (cf. Section 4.4).

Table 8.15 gives the proportion of intra-Michigan transitions during 1945-1967 to four occupational categories by migrant farm background of the respondent for those leaving a job as an operative, nonfarm laborer, or farm laborer. On the basis of the computed χ^2 values, the occupational destination of a respondent leaving a job as a nonfarm laborer or farm laborer was unaffected by the respondent's migrant farm background. But apparently migrant farm background did affect the occupation entered by those leaving jobs as operatives. In particular, respondents with no migrant farm background were more likely to reenter a job as an operative and less likely to enter a job categorized

Table 8.14 Proportion of intra-Michigan transitions to four occupational categories by previous occupation and by the location in which the respondent was reared, 1945-1967.

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	Location reared: Texas	Mich.	Location reared: Texas	Mich.	Location reared: Texas	Mich.
Operative	.633	.548	.453	.519	.544	.400
Nonfarm laborer	.128	.104	.289	.250	.167	.267
Farm laborer	.025	.061	.063	.096	.114	.100
Other occupations	.214	.287	.195	.135	.175	.233
TOTAL PROPORTION DOWN	1.000	1.000	1.000	1.000	1.000	1.000
TOTAL N	281	115	128	52	114	30
χ^2, 3 d.f.	6.2		1.9		2.7	

Table 8.15 Proportion of intra-Michigan transitions to four occupational categories by previous occupation and by migrant farm background, 1945-1967.

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	M.F. Background?		M.F. Background?		M.F. Background?	
	No	Yes	No	Yes	No	Yes
Operative	.655	.534	.500	.421	.479	.553
Nonfarm laborer	.119	.124	.274	.301	.229	.175
Farm laborer	.026	.049	.048	.090	.104	.105
Other occupations	.201	.293	.179	.188	.188	.167
TOTAL PROPORTION DOWN	1.001	1.000	1.001	1.000	1.000	1.000
TOTAL N	194	266	84	133	48	114
χ^2, 3 d.f.	8.1		2.1		0.9	

as other occupations. While the large size of the χ^2 value for the subtable on operatives cannot be attributed to expected cell frequencies less than five, the observed dependency may derive from the high correlation between the educational level and migrant farm background of the respondents. Unfotunately the number of observations is insufficient to warrant more detailed cross-tabulations.

8.5 Findings concerning the correspondence between the theoretical construct time t and observable measures of time

Calendar time may introduce variation into conditional transition probabilities because of fluctuations with calendar time in either the vacancy structure or the attraction of a particular transition. If the proportion of employed males in different occupations in Michigan (cf. Table 8.16) is used to approximate the vacancy strcture in that location, then the proportion of vacancies in Michigan appears to have been comparatively stable for operatives and nonfarm laborers but to have decreased markedly for farm laborers during 1935-1967.

Table 8.16 Proportion of males employed in different occupations in Michigan, by year.[3]

	1940	1950	1960
Operatives	.203	.243	.220
Nonfarm laborers	.084	.064	.058
Farm laborers	.046	.020	.011
Other occupations	.668	.674	.712
TOTAL PROPORTION DOWN	1.001	1.001	1.001
TOTAL N in 000's	1418	1765	1822

[3]This table is based on Table 5.4.

Table 8.17 shows the estimate of the attraction of four occupational destinations for intra-Michigan transitions from jobs as an operative, nonfarm laborer, and farm laborer for 1935-1944, 1945-1954, and 1955-1967. These figures suggest that over the period 1935-1967 for respondents leaving all three occupations, the attraction of a job as an operative declined slightly, but the attraction of a job as a nonfarm laborer or farm laborer increased. This means that respondents in Michigan have been increasingly attracted to jobs among the very lowest in social prestige over the period 1935-1967. This unfavorable trend implied by Table 8.17 is, of course, a very tentative conclusion due to the unsatisfactory nature of the approximation used in calculating the estimates of the attraction of a transition.

Table 8.18 reports the proportion of intra-Michigan transitions during 1945-1967 to four occupational categories by the respondent's age for those leaving a job as an operative, nonfarm laborer, or farm laborer. Since $\chi^2_{.05,3} = 7.8$ and the observed values of χ^2 are less than this for all three subtables in Table 8.18, one cannot reject the hypothesis that the occupational destination was independent of age. I did not anticipate this finding, nor the generally inconsistent effect which age appears to have on the attraction of a particular occupation for those leaving the three occupations.

Table 8.19 displays the proportion of intra-Michigan transitions during 1945-1967 to four occupational categories by duration in the previous occupation for respondents leaving a job as an operative, nonfarm laborer, or farm laborer. On the basis of the computed values of χ^2, duration in a job as a nonfarm laborer or farm laborer did not significantly influence the occupation entered by the respondent, and

Table 8.17 Attraction of intra-Michigan transitions to four occupational categories by previous occupation and by calendar year.

	Previous occupn: Operative		
Occupational Destination	1935-1944	1945-1954	1955-1967
Operative	3.2	2.8	2.4
Nonfarm laborer	1.5	2.0	2.1
Farm laborer	1.1	1.7	3.7

	Previous occupn: Nonfarm laborer		
Occupational Destination	1935-1944	1945-1954	1955-1967
Operative	2.6	2.2	1.9
Nonfarm laborer	2.6	3.7	5.4
Farm laborer	0.0	2.4	7.4

	Previous occupn: Farm laborer		
Occupational Destination	1935-1944	1945-1954	1955-1967
Operative	2.8	1.9	2.1
Nonfarm laborer	1.9	2.4	4.0
Farm laborer	4.1	7.1	5.6

Table 8.18 Proportion of intra-Michigan transitions to four occupational categories by previous occupation and by age, 1945-1967.

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	Age in years: 16.0-24.9	25.0-49.9	Age in years: 16.0-24.9	25.0-49.9	Age in years: 16.0-24.9	25.0-49.9
Operative	.575	.590	.394	.504	.488	.577
Nonfarm laborer	.156	.102	.279	.301	.250	.128
Farm laborer	.060	.027	.087	.062	.095	.115
Other occupations	.210	.280	.240	.133	.167	.179
TOTAL PROPORTION DOWN	1.001	0.999	1.000	1.000	1.000	0.999
TOTAL N	167	293	104	113	84	78
χ^2, 3 d.f.	7.5		5.4		3.9	

Table 8.19 Proportion of intra-Michigan transitions to four occupational categories by previous occupation and by duration in previous occupation, 1945-1967.

Occupational Destination	Previous occupn: Operative		Previous occupn: Nonfarm laborer		Previous occupn: Farm laborer	
	Years duration: 0.1-1.9	2.0-49.9	Years duration: 0.1-1.9	2.0-49.9	Years duration: 0.1-1.9	2.0-49.9
Operative	.594	.572	.453	.449	.534	.523
Nonfarm laborer	.143	.093	.284	.304	.203	.159
Farm laborer	.049	.026	.095	.029	.102	.113
Other occupations	.214	.309	.169	.217	.161	.205
TOTAL PROPORTION DOWN	1.000	1.000	1.001	0.999	1.000	1.000
TOTAL N	266	194	148	69	118	44
χ^2, 3 d.f.	7.9		3.4		0.7	

in particular, did not, as I predicted in Section 4.5, increase noticeably the likelihood of a transition to the same occupation. On the other hand, duration in a job as an operative apparently had a nonnegligible effect on the occupational destination as the observed χ^2 for this subtable is expected less than five times in a hundred in a random sample. Table 8.19 shows that respondents who had been an operative for two or more years were especially likely to enter jobs categorized as other occupations. Since this category includes craftsmen and foremen, this finding offers no surprise.

8.6 Findings concerning the validity of the Markov assumption

Table 8.20 presents the proportion of intra-Michigan transitions to four occupational categories during 1945-1967 by previous occupation y_j and by occupation y_i held prior to y_j. Since $\chi^2_{.05,9} = 16.9$ and since the calculated values of χ^2 for those leaving jobs as operatives and nonfarm laborers is, respectively, 54.5 and 18.7, the conditional probability of a transition to occupation y_k apparently depended on the occupation y_i held prior to occupation y_j when y_j is either operative of nonfarm laborer. However, if occupation y_j is classified as farm laborer, then the null hypothesis that occupation y_k was independent of y_i cannot be eliminated as a reasonable possibility. Moreover, for the subtable on respondents leaving a job as a nonfarm laborer, the expected cell frequencies for an occupational destination as farm laborer are less than the ordinarily desired value of five for all four categories of occupation y_i. Hence the null hypothesis also cannot be rejected with any degree of confidence when y_j is nonfarm laborer.

In Section 4.6 I predicted that

Table 8.20 Proportion of intra-Michigan transitions to four occupational categories by previous occupation y_j and by occupation y_i held prior to y_j, 1945-1967.

	Occupation y_j: Operative				Occupation y_j: Nonfarm laborer				Occupation y_j: Farm laborer			
Occupational Destination	Occupation y_i: Oper.	Nf.L.	F.L.	Other	Occupation y_i: Oper.	Nf.L.	F.L.	Other	Occupation y_i: Oper.	Nf.L.	F.L.	Other
Operative	.732	.517	.485	.462	.638	.426	.333	.536	.571	.541	.585	.571
Nonfarm laborer	.065	.233	.167	.115	.234	.370	.357	.214	.190	.297	.098	.048
Farm laborer	.024	.033	.136	.000	.021	.019	.167	.071	.048	.108	.146	.095
Other occupns.	.179	.217	.212	.423	.106	.185	.143	.179	.190	.054	.171	.286
DOWN, TOTAL PROPORTION	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000	0.999	1.000	1.000	1.000
TOTAL N	168	60	66	78	47	54	42	28	21	37	41	21
χ^2, 9 d.f.	54.5				18.7				13.0			

(8.5) $$\alpha_{y_k x_j y_j x_k | y_k}(t) > \alpha_{y_i x_j y_j x_k | y_k}(t),$$

where occupation $y_i \neq y_k$ and i, j, and k are the states consecutively occupied by the individual. According to this prediction, the diagonal element should be the largest element in each row of all three subtables of Table 8.20; inspection reveals that this does occur in fourteen of sixteen rows. This suggests that the attraction of a transition to occupation y_k not only increases when occupation y_j is identical to y_k, but also increases when occupation y_i is identical to y_k for occupation y_j fixed.

Although these findings are far from conclusive, they support my argument in Section 4.6 that the Markov assumption is invalid insofar as the conditional probability of an intrastate transition from occupation y_j to occupation y_k is concerned. Because a decision on the validity of the Markov assumption has great consequence for the direction taken in developing stochastic models of job mobility, future investigations should place a high priority on establishing with some degree of certainty whether or not the conditional transition probability $q_{x_j y_j x_k | y_k}(t)$ depends on the occupation, industry, and location of state i.

CONCLUSION

This research has had two main aims: (1) to analyze and compare previously-proposed stochastic models of social mobility possessing a Markovian interpretation, and (2) to apply these models, insofar as possible, to job mobility of a sample of 584 Mexican-American men with a high school education or less who resided in selected Michigan counties during the winter of 1967-1968.

Summary

An early task was to show that it is permissible to separate the process of individuals leaving a social position from the process of individuals entering a new social position, given that they are leaving some other social position. Division of the overall mobility process into these two subprocesses facilitated my comparison of stochastic models of social mobility and enabled me to examine the impact of different variables on job mobility of the sample in a much more detailed fashion.

The innovative features of most previously-proposed stochastic models of social mobility have pertained to the process of individuals leaving a social position. It seems natural to assume that an individual's probability of leaving a social position is a time-independent constant; I designated this Probability Law I. Other investigators have consistently reported that predictions based on this probability law described their observations on social mobility poorly. Three

general approaches have been used to develop models giving better predictions: the assumption of nonstationarity (time-dependence), the assumption of population heterogeneity, and the assumption of stages within a social position. Each approach has been used to construct various models of the process of an individual leaving a social position. Together these models imply six probability laws as alternatives to Probability Law I; all have been reported by others to give improved predictions of social mobility.

Construction of a satisfactory mathematical model is only part of the task of explaining the process of an individual leaving a social position. Since the mathematical models are intended to describe equivalent events, i.e., equivalent individuals leaving equivalent social positions at equivalent points in time, identifying such equivalent events is also necessary to the explanation. Systematic work on this has not been prominent in earlier studies.

In the present research a job was conceived as the basic social position. This conception has heuristic benefits and also provides a reasonable basis for a substantive understanding of social mobility. The analytic framework employed in the discussion on the identification of equivalent events focused on the jobholder and employer evaluating the match between the jobholder and his job in terms of the satisfaction provided by the present match and opportunities for a more satisfactory match. I discussed how the following variables might affect the rate of leaving a job: the occupation, industry, and geographical location of the job; the jobholder's educational level, the geographical location in which he was reared, his migrant farm background, his age at beginning the job, his duration in the job, and

his previous work experiences; and the calendar year.

This report does not include a separate review of work on the process of individuals entering a new social position because of the limited attention that this topic has received previously. After a short discussion of a technical complication that results from conceiving a job as the basic social position, I considered simple mathematical models of the conditional probability of an individual moving from one job to another. Fundamental quantities in these models are the distribution of vacancies among different types of jobs and the attraction of a particular type of job for individuals with particular attributes who are leaving jobs with particular attributes. Since job vacancies are rarely enumerated directly, I demonstrated that under certain conditions the distribution of job vacancies can be approximated by the distribution of filled jobs; I also examined possible ways of estimating job vacancies from other information.

Most attention was directed to the impact of different variables on the attraction of a particular type of job. My arguments were based on the assumption that job-seekers and employers select the most satisfactory situation of those perceived to be available. Among the variables discussed were the following: the occupation, industry, and geographical location of the jobs entered and left, the job-seeker's educational level, the geographical location in which he was reared, his migrant farm background, his age at the time of the transition, his duration in the previous job, and his previous work experiences; and the calendar year.

I tested my hypotheses and six of seven previously-proposed probability laws using continuous-time work histories gathered by

Choldin and Trout (1969). I restricted my investigation to those 584 Mexican-American men with twelve or fewer years of completed schooling who had relatively complete work histories. I refer to these men as the respondents. Because the respondents represent a population residing in a comparatively small geographical area, my findings cannot be generalized to a larger population of any widespread interest. At best they suggest what one might expect for individuals not residing in the sample counties at the time of the interviews, but otherwise closely resembling the respondents.

I found that in general the occupation of the job and the jobholder's educational level most affected the rate at which respondents left jobs. The geographical location of the job was extremely important for migratory farm laborers but otherwise had only a slight influence. The industry of the job aided in discriminating among operatives, but not nonfarm laborers. The location in which the jobholder was reared was more important than educational level in the case of operatives in fabricated metal and motor vehicle manufacturing in Michigan; the contrary was true for all other occupations examined. The independent effect of a migrant farm background appeared negligible in all instances.

I also found the rate of respondents leaving a job to be relatively stable over 1935-1967 except for operatives, for whom 1935-1944 differed markedly from 1945-1967, and also nonfarm laborers, for whom 1960-1967 possibly differed from 1935-1959. To my surprise the age of the jobholder at the beginning of the job had no noticeable effect on the rate of leaving the job. I suggested possible explanations for this interesting result.

Previous nonagricultural experience had a major impact on the rate at which respondents left a job as a migratory farm laborer in Texas. This finding was inferred by comparing the effects on the rate of leaving the job of previous occupation and industry experiences and the number of previous sequences. Apparently my original hypothesis concerning the influence of previous work experiences on the rate of leaving the job was incorrect; in the light of my finding for migratory farm laborers in Texas, I reformulated the hypothesis, suggesting that the relative change in job status was the key factor.

My findings on the identification of equivalent respondents leaving equivalent jobs gave twenty-one sets of data for evaluating the seven previously-proposed probability laws. One of these probability laws was disregarded because of computational difficulties; maximum likelihood estimates of parameters reduced two others to one of the remaining four probability laws. Probability Law I, which postulates a time-independent rate of leaving the job, appeared entirely satisfactory for four of the twenty-one data sets. However, predictions for the other seventeen data sets were noticeably and in my judgment significantly improved with one or more of the other three probability laws. This improvement implies that the rate of leaving the job depended on the duration in the job. Of these three probability laws, the one derived from a two-stage model of a job, which I designated Probability Law V, gave consistently, although only slightly, better predictions than the other two.

Except for Probability Law I, each probability law examined can be derived from more than one of the three general approaches that have been used (i.e., the assumptions of nonstationarity, of

population heterogeneity, and of stages within a social position). With the data available in this study, models based on different approaches cannot be empirically discriminated in an unambiguous fashion. However, the parameter estimates of a probability law can be used to solve for the parameters of various models. Since the dependence of the parameters of a particular model on attributes of jobs and respondents should reflect the hypotheses made about the effect of these variables on the process of an individual leaving a job, comparing estimates of the parameters of a model for different data sets permits an evaluation of the model. From a substantive point of view, the two-stage model of a job that leads to Probability Law V seemed particularly worthy of further investigation.

Findings on the process of respondents entering a new job centered on which variables influenced the attraction of respondents to different jobs. The variables most significantly affecting this attraction were the geographical location and occupation of the jobs entered and left, and the jobholder's educational level. Noticeable changes in attractions occurred during 1935-1967; this indicates that the calendar year of the transition should not be disregarded. On the other hand, evidence could not rule out the null hypothesis that the attraction of respondents to different occupations was independent of the industry of the job left, the location in which the jobholder was reared, and the jobholder's age at entering the new job.

Results for migrant farm background, the duration in the job left, and the occupational category of the job held prior to the one being left were more complicated: the attraction of respondents to different occupations in a given location significantly depended on

these variables when respondents left jobs as operatives but not jobs as farm laborers, or, for the first two variables, jobs as nonfarm laborers. The evidence on the third variable was inconclusive when respondents left jobs as nonfarm laborers because of several unusually low expected cell frequencies. In this, as well as several other instances, more observations would have been highly desirable in order to place greater confidence in the findings. Such additional observations would also have permitted further cross-classifications that might have clarified the effects of different variables, e.g., the interrelationship between the job-seeker's educational level and his previous work experiences.

In evaluating the influence of the geographical location and occupation of the job entered and the calendar year of the transition on the attraction of different jobs, it was necessary to approximate the distribution of job vacancies by the estimated distribution of filled jobs. The adequacy of this approximation was assessed by comparing estimates of the crude vacancy rates for different groups in different jobs. Since estimates were made for only a small and unrepresentative fraction of the overall population in any given location, the results were inconclusive, but they suggested that the approximation was very rough and should be avoided if possible.

Conclusions

To conclude this study we should briefly consider several areas that deserve further exploration in the light of the work reported here. First of all, it seems worthwhile to repeat the empirical part of the analysis on other populations. The addition of other

variables pertaining to the attributes of individuals and of jobs would be beneficial. Variables of particular interest that were omitted in this study include the jobholder's sex, ethnicity, and family background, and the wage level and social prestige associated with the job. While replications of this type would serve to generalize and extend the range of the findings of the present research, they would not necessarily alter the structure of my analysis or of the research methods that I have used.

Several theoretical issues of fundamental importance require special mention. This study is somewhat unusual in applying stochastic models to job mobility rather than to mobility between occupations, industries, geographical areas, or social prestige categories. I argued that conceiving a job as the basic social position in the system provides an excellent basis for a substantive explanation of mobility. Moreover, I demonstrated (cf. Section 3.1) that more comprehensive social locations, e.g., social prestige categories, can be decomposed into sequences of jobs. If desired, models of job mobility can be reconstructed to form models of the other types of social mobility mentioned above. While models based on more comprehensive categories may continue to be useful in making broad comparisons of mobility systems, e.g., between different societies or periods of history, my findings suggest that such models may not mirror very accurately the finer structure of the mobility process. It seems clear that we need to consider further the conceptualization of social positions in a social system, and especially to reflect on the implications of a theory in which the basic unit of analysis is, for example, a job rather than a prestige category.

Most stochastic models of social mobility have assumed that the Markov assumption is valid. In this study I raised two separate questions pertaining to this assumption: (1) do attributes of job i held prior to job j affect the rate of leaving job j, and (2) do attributes of job i affect the attraction of individuals to a new job k. My results gave both affirmative and negative answers to each question. Given the heavy reliance of stochastic models of social mobility on the Markov assumption, there is a manifest need for re-examining the effect of previous experiences on the process of leaving a social position and on the process of entering a new social position. Such investigations can be expected to influence significantly the future direction of work on models of social mobility.

It is generally acknowledged that social mobility is time-dependent. In this research I discussed and attempted to discover whether time should be conceptualized as the calendar year, the individual's age, or the duration in a social position. Since the structure of the social system, e.g., the distribution of job vacancies, fluctuates from year to year, calendar time can not ordinarily be ignored. Hence the main issue here is whether the dissolution and formation of a match between an individual and a social position depends on the age of the individual, on the duration of the match, or on both. My findings indicate that both the process of leaving a job and the process of entering a new job were often considerably affected by the duration of the match, but had little or no dependence on the respondent's age at the time of the move when duration was controlled. Since my findings contravene the importance usually attributed to the individual's age, the independent effects of age and duration should

be tested more rigorously.

My analysis showed that previous models of social mobility developed to improve upon the stationary Markov model have concentrated on the process of individuals leaving a social position. Furthermore, I showed that several different models implied the same probability law as the description of the leaving process. While I tested different probability laws in this research, I was unable to discriminate empirically among different models leading to the same probability law. Since my results indicated that several probability laws can satisfactorily predict the observed rate of leaving a job when sufficient care is given to the identification of equivalent individuals and equivalent jobs, we do not presently need a further proliferation of probability laws. Rather we need substantive specification and empirical assessment of the various models from which the previously-proposed probability laws can be derived.

with a few exceptions previous work has ignored models of the process of individuals entering a new social position, given that they are leaving some other social position. Although I outlined a simple mathematical model that may serve as a starting point for work in this area and undertook a preliminary empirical investigation, additional theoretical and empirical work is greatly needed. One fundamental quantity in this model is the distribution of job vacancies; due to difficulties in directly enumerating job vacancies, the estimation of job vacancies needs special attention.

While I succeeded in demonstrating that stochastic models based on a conception of individuals moving among social positions do not inevitably ignore the vacancy concept to which White (1968, 1969,

1970) has called our attention, I was unable to show that the distribution of unattached, e.g., unemployed, persons is comparable in importance to the distribution of job vacancies. My silence on this subject primarily resulted from the inadequacy of the data used in this research for any consideration of unemployment. However, much of my analysis could, with minor modifications, be applied to a system of job mobility including unemployment as a recognized state.

Although I am reasonably satisfied with the research design used in this study and am especially pleased with the results obtained by separating the process of individuals leaving a social position from the process of individuals entering a new social position, several changes could be made in the research methods.

My efforts to identify equivalent individuals and equivalent jobs, or alternatively stated, to identify those variables significantly differentiating events, were based upon cross-classification of independent variables. The primary disadvantage of cross-classification of variables is that it is ordinarily impossible to obtain sufficient data to control simultaneously all relevant variables.

Multiple regression analysis provides an alternative approach that has previously been proposed (Coleman, 1970; Morrison, 1970). This too presents problems. Regression analysis is usually used where the effects of independent variables are additive; however, some of my findings indicate that this condition is not met in either the process of an individual leaving a job or the process of an individual entering a new job. While some degree of nonadditivity of independent variables can be accommodated in regression, the analysis becomes quite complex and acquires some of the faults of cross-classification

when the extent of nonadditivity is great. This should serve as a caution rather than a ban on the use of regression analysis to identify variables differentiating individuals and jobs in the mobility process.

An additional caution is in order when regression analysis is used to study the process of individuals leaving a social position. Suppose that this process depends on duration and that the two-stage model of leaving a social position that leads to Probability Law V (cf. Figure 7.19) describes the process. The standard postulate would be that the five independent parameters of the two-stage model are linear functions of certain independent variables pertaining to attributes of jobs and jobholders. But, since the three parameters of Probability Law V are nonlinear functions of the five parameters of the two-stage model (cf. equation (7.22)), such a postulate implies that the parameters of Probability Law V are nonlinear functions of the independent variables. This problem can be avoided with certainty only if Probability Law I describes the process of an individual leaving a social position; however, the results of this research indicate that this condition is not usually fulfilled. Thus, if regression analysis is applied to the study of the process of individuals leaving a social position, the complications introduced by nonlinearity in a regression model must be confronted.

Because of the problems arising from the use of regression analysis, cross-classification of variables may continue to be useful for some time. In this case there is a definite need for an improved method of identifying the variables most affecting the rate of leaving a job. In this research I identified such variables by comparing

plots of survival curves, i.e., by comparing the proportions remaining in a job after duration t plotted against duration t. This method has two main disadvantages: (1) judgments of differences are based upon visual inspection rather than upon less arbitrary measures; (2) the method requires extensive plotting that I found very expensive and time-consuming even when done by a computer. Yet the method does permit an evaluation of the shape of a survival curve, a feature often hidden by a single summarizing measure. What is needed is a method which retains this advantage but eliminates the arbitrariness of personal judgment and the expense of plotting the data.

Except for Probability Law I, I did not use tests of statistical significance to evaluate the goodness of fit of the different probability laws examined. I also did not establish confidence intervals for the parameters of the probability laws. These tasks, not entirely unrelated to that discussed in the preceding paragraph, present complicated statistical problems that deserve consideration at some future time.

While methodological improvements and refinements are highly desirable, they must not be allowed to divert attention from the primary sociological goal: the construction of a theory of social mobility. Most previous stochastic models of social mobility have not emerged from an attempt to understand the underlying social processes, but from an attempt to capture patterns in data with mathematical equations. This situation must be rectified.

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APPENDICES

APPENDIX A

Interview Schedule for Work Histories

(Supplement Series 16, 17)

Ahora, quisiera que me dijera algo acerca de los diferentes trabajos que ha hecho y de los diferentes lugares en que ha vivido. Hasta ahora hemos hablado de estas cosas pero sólo hasta que usted cumplió 16 años. Ahora vamos a empezar después que cumplió 16 años.

Now, I'd like you to tell me something about the different work you have done and the different places where you have lived. I tell you we've been talking about before you were 16 years old. Now let's start when you were 16 years old.

1.- En dónde estaba su hogar cuando tenía 16 años?
2. Cuando tenía 16 años hizo Ud. cualquier clase de trabajo estando dicerni--ya sea.

--todo el tiempo o parte del tiempo?...
--por todo el año o sólo por un tiempo?...
--en la ciudad, en un rancho, o en la labor con los aparatos?...

Durante algunas de estas ocupaciones quisiera saber de cualquier servicio militar que haya tenido...

--o de cualquier promoción que haya recibido Ud. en el ejército, mientras trabajaba con esa clase ocupación...
--y de los tiempos que estuvo desempleado entre un trabajo y otro.

1. Where was your home when you were 16 years old?
2. When you were 16 (if not, so any kind of work for which you were paid in money? Either:

--full-time or part-time?...
--for the whole year or just for a short while?...
--in town, on a ranch, or in the fields with the tractors?...

Also as we talk I'd like you to tell me if you've had any military service...

--or about any promotions you may have got while working in the same occupa...

--and any periods of unemployment between jobs.

INTERVIEWER: USE THE SPACE BELOW WHICH YOU FEEL IT WILL BE NECESSARY TO RECORD THE INFORMATION FOR THE RESPONDENT, FROM THE TIME HE WAS 16 YEARS OLD UP TILL JUST BEFORE HE ESTABLISHED PERMANENT RESIDENCE IN MICHIGAN.

A's Age	(A) Where Resided (Nearest City/Town)	(B) State or Country	(C) Migrant Farm Work: In What States Worked in Dairy Farm Work	(D) Non-Farm Work: Type of Work Done (Be Specific)	(E) Unemployment & Military Service: Kind of Work Looking for	Kind of company Duration of Unemployment or Military Service	Business Worked During (Yr. or Year)	Size
16								

INTERVIEWER: AT THE POINT WHERE RESPONDENT MOVED TO MICHIGAN PERMANENTLY, GO TO NEXT PAGE -7-

QUESTION SERIES No. 15

INTERVIEWER: THESE QUESTIONS SHOULD BE ASKED FOR RESIDENCES AND JOBS RECORDED AT THE POINT WHERE THE RESPONDENT HAS ESTABLISHED PERMANENT RESIDENCE IN MICHIGAN.

RESIDENCE: IF RESIDENCE WAS IN Michigan OBTAIN ONLY THE NAME OF THE TOWN.
IF RESPONDENT left Michigan TO RESIDE IN ANOTHER STATE AT ANY TIME, OBTAIN BOTH State & Town.

FOR NON-MIGRANT WORK

(1) ¿Qué clase de trabajo hizo usted? (OBTENGA UNA DESCRIPCION DE SU TIPO DE LABOR)
(2) En qué clase de negocio o compañía trabajó usted? (O SEA LA ACTIVIDAD COMERCIAL QUE LA CARACTERICE)
(3) Por lo general, cuántas horas a la semana trabajó usted en ese empleo?
(4) Cuál era su pago por semana en ese empleo?
(5) For cuánto tiempo tuvo ese empleo? (AÑOS/MESES)

FOR NON-MIGRANT WORK

(1) What kind of work did you do? (OBTAIN A DESCRIPTION OF HIS TASKS)
(2) What kind of business or company did you work for? (TYPE OF BUSINESS ACTIVITY OF EMPLOYER)
(3) On the average, how many hours a week did you work on that job?
(4) What was the average weekly pay at that job?
(5) How long did you have that job? (YEARS/MONTHS)

FOR MILITARY SERVICE (Enter as Non-Migrant Work)

(1) Cuál era su clasificación o "job specialty"? (ENTER UNDER "OCCUPATION" (1))
(2) Cuál fué el "rank" más alto que logró en el servicio? (ENTER UNDER "KIND OF BUSINESS"(2))
(5) For cuánto tiempo estuvo en el servicio "on active duty"? (ENTER UNDER "DURATION" (5))

FOR MILITARY SERVICE (Enter as Non-Migrant Work)

(1) What was your job specialty or classification? (ENTER UNDER "OCCUPATION") (1))
(2) What was the highest rank you reached while in the service? ENTER UNDER "KIND OF BUSINESS" (2)
(5) How long were you in service on active duty? (ENTER UNDER "DURATION" (5))

INTERVIEWER: PUT AN ASTERISK (STAR) IN THE LEFT MARGIN ALONGSIDE THE LINE REFERRING TO MILITARY

FOR FARM LABOR WITH THE MIGRANTS

INTERVIEWER: IN ORDER TO MAKE CERTAIN THAT THE RESPONDENT DOES NOT HAVE SUCH WORK, BECAUSE IT MAY HAVE BEEN FOR ONLY A SHORT DURATION, EACH SUMMER, YOU MAY HAVE TO ASK ABOUT THIS SEPARATELY FOR EACH YEAR. DO NOT ASSUME THAT JUST BECAUSE A RESPONDENT MAY NOT HAVE WORKED IN "LA LABOR" DURING THE FIVE OR TEN YEARS (OR SUMMERS) IN MICHIGAN THAT HE TAKES/OPE NEVER DID SO AT A LATER TIME.

(6) Cuando usted vivía en...(ciudad) (pueblo)... y mientras trabajaba en...(en donde trabajaba, si tenía otro empleo)...hizo ud. cualquier labor de rancho?

IF "YES", ASK:
(7) En dónde trabajó ese año? (OBTENGA ESTADO)
(8) For cuánto tiempo, en total, trabajó durante ese año? (OBTAIN MONTHS & WEEKS)
(9) Algún otro miembro de su familia trabajó con usted ese año? (OBTAIN POSITIONS IN THE FAMILY OF THOSE WHO WORKED, SUCH AS: WIFE, CHILDREN, OTHER RELATIVES LIVING IN HIS HOUSE, ETC.)
(10) Trabajó usted el tiempo completo cada día, o sólo en fines de semana, o en sus vacaciones, o durante un "changeover" o "lay off",o una huelga, o qué?
(11) En dónde se quedó usted mientras trabajaba en la labor ese año?--en su casa en... (ciudad o pueblo de residencia)..., en el rancho en donde estaba trabajando, o en la casa de alguien que vivía cerca del rancho?

FOR FARM LABOR WITH THE MIGRANTS

(6) When you lived in...(city) (town)...and while you were working at...,job where was working, if had another job ...did you do any farm labor in the fields?

IF "YES", ASK:
(7) Where did you work that year? (OBTAIN STATE)
(8) How long did you work, in total, during that year? (OBTAIN MONTHS & WEEKS)
(9) Did any other members of your family also work with you that year? (OBTAIN POSITIONS IN THE FAMILY OF THOSE WHO WORKED, SUCH AS: WIFE, CHILDREN, OTHER RELATIVES LIVING IN HIS HOUSE, ETC.)
(10) Did you work full-time every day, or only on weekends, or during your vacation, or during a changeover or lay off at the plant, or during a strike, or what?
(11) Where did you stay while doing farm work that year?--at home in... town of residence)..., on the farm where you were working, or at the home of someone else who lived nearby the farm?

INTERVIEWER: USE THE LINES BELOW WHICH YOU NEED TO RECORD THE INFORMATION ABOUT THE RESPONDENT, BEGINNING AT THE POINT WHERE THE RESPONDENT ESTABLISHED PERMANENT RESIDENCE IN MICHIGAN UP TO THE PRESENT

R's Age	Where RESIDENCE was (City/Town)	NON-MIGRANT WORK Including MILITARY Service and Periods of Unemployment (1) Occupation: Type of Job or Service Specialty	(2) Kind of Business or Business Worked for (or highest Ser. Rank)	(3) Av. hrs. work per wk.	(4) Dura-tion	(5)	MIGRANT FARM LABOR (for any duration) (6) In any labor on farm or field w/ migrants	(7) What State(s)	(8) Dura-tion	(9) Did your family work too? (Who?)	(10) Everyday? Weekends? Vacation? Changeover Strike?	(11) Where lived
							No Yes					
							No Yes					
							No Yes					
							No Yes					
							No Yes					
							No Yes					
							No Yes					
							No Yes					
							No Yes					
							No Yes					
							No Yes					
							No Yes					

APPENDIX B

Rules for Editing and Coding Job Histories

APPENDIX B

Rules for Editing and Coding Job Histories

1. Use the following format:

Sequence # Date Age Duration Occupation (primary/secondary)

2. Begin by noting for sequence #0:

(a) Date of interview to the nearest tenth of a year (p. 1 of interview schedule).

(b) Present age (p. 3 of interview schedule). Adjust age x to x.5 years unless birthdate or other information is given which permits a more accurate designation of present age.

(c) Present occupation (p. 3 of interview schedule).

3. Determine the number and order of sequences:

(a) A new sequence begins whenever the respondent changes his residence (excluding intracity moves), occupation, or employer. Treat consecutive periods of migratory farm labor in different locations as one sequence unless the respondent changes his permanent residence or "home base."

(b) Treat a period of unemployment as a separate sequence. Do not treat a lay-off or vacation as a new sequence if the respondent returns to his former job.

(c) Treat as one sequence with a primary and secondary occupation whenever (1) the respondent holds two jobs simultaneously, or (2) he has a repeated pattern of seasonal occupations that lasts for more than one year. Treat as the primary occupation the job held for the most hours per week in the first case and the job held the longest period of time in a year in the second case.

4. Number the jobs consecutively beginning with the current job as number one. Write down the primary and secondary occupation for each sequence.

5. For each sequence record to the nearest tenth of a year the duration of the sequence, the age of the respondent at the beginning of the sequence, and the date at the beginning of the sequence.

6. In order to obtain a continuous time history, the following adjustments may be made:

(a) Present age x may be x.0 to x.9 years.

(b) Duration may be increased or decreased by 10 percent of the reported value or one year, whichever is less. Age and date should be adjusted correspondingly so that overall consistency and continuity are maintained.

(c) A sequence of "no information" may be inserted if it seems that information was not gathered for some period or if the above procedure still leaves some of the respondent's history unaccounted for.

(d) The duration of the present job is sometimes reported as "to the present" and should be calculated as the difference between the date of the interview and the termination of the previous sequence. Apparently a number of interviewers used this procedure in the field rather than ask the respondent how long he had held his present job. Because interviewers who used this procedure frequently miscalculated the duration of the most recent sequence, a somewhat more liberal adjustment may be made for the duration of this sequence than is stated in (b).

7. Check that:

(a) The sum of the durations = present age - 16.0 = date of interview - date of the sequence for age 16.0.

(b) The duration of a sequence = difference in ages for successive sequences = difference in dates of successive sequences.

8. Use any additional information in the interview that helps to pin down the date, age, or duration for a sequence.

APPENDIX C

Least Squares Parameter Estimates

Table C.1 Statistics pertaining to least squares parameter estimates for Probability Law I.

Data set	$n_j(0)$	κ	S_I	$-\ln L_I$
Aa	42	2.916	.049	23.579
Ab	71	1.689	.117	86.739
Ac	57	1.247	.083	104.711
Ba	83	.943	.181	153.300
Bb	103	.273	.038	251.614
Ca	130	.845	.022	167.675
Cb	209	.526	.174	383.220
Cc	129	.336	.117	280.830
Da	22	.592	.036	37.593
Db	97	.338	.057	192.586
Dc	71	.219	.043	171.538
Ea	38	.917	.099	49.741
Eb	18	.174	.428	33.543
Ec	39	.311	.069	70.623
Ed	122	.134	.865	254.058
Ee	24	.118	.049	47.365
Fa	41	.414	.173	84.194
Fb	170	.127	.423	309.405
Fc	38	.170	.079	58.418
Fd	24	.114	.039	39.096
Fe	32	.058	.287	58.245

Table C.2 Statistics pertaining to least squares parameter estimates for Probability Law II.[1]

Data set	$n_j(0)$	δ	θ	S_{II}	$-\ln L_{II}$
Aa	42	-	-	-	-
Ab	71	2.127	1.025	.096	68.390
Ac	57	2.554	1.647	.063	70.126
Ba	83	1.171	.739	.030	124.896
Bb	103	4.480	14.401	.021	250.067
Ca	130	9.592	10.642	.019	163.274
Cb	209	1.661	2.129	.032	357.176
Cc	129	1.947	4.155	.032	271.484
Da	22	2.541	3.525	.026	36.056
Db	97	-	-	-	-
Dc	71	-	-	-	-
Ea	38	1.286	.915	.013	40.769
Eb	18	.349	.225	.133	30.571
Ec	39	1.908	4.752	.020	66.681
Ed	122	.728	2.186	.208	222.994
Ee	24	-	-	-	-
Fa	41	.958	1.500	.043	60.896
Fb	170	1.366	6.807	.209	287.813
Fc	38	1.645	7.447	.029	53.345
Fd	24	-	-	-	-
Fe	32	-	-	-	-

[1]Blanks indicate that the least squares estimate of parameters reduced the probability law to Probability Law I.

Table C.3 Statistics pertaining to least squares parameter estimates for Probability Law IV.[2]

Data set	$n_j(0)$	ξ	ω	ϕ	S_{IV}	$-\ln L_{IV}$
Aa	42	-	-	-	-	-
Ab	71	.073	1.933	.661	.087	69.824
Ac	57	.025	1.503	.468	.057	68.220
Ba	83	.247	1.281	1.126	.026	122.976
Bb	103	.180	.138	.211	.021	249.868
Ca	130	.000	.903	.091	.019	162.634
Cb	209	.244	.593	.793	.025	358.342
Cc	129	.189	.315	.523	.029	271.173
Da	22	.488	.705	5.664	.020	37.311
Db	97	-	-	-	-	-
Dc	71	-	-	-	-	-
Ea	38	.287	1.099	1.099	.011	40.945
Eb	18	.087	1.732	3.765	.059	27.764
Ec	39	.119	.283	.278	.019	66.442
Ed	122	.067	.332	.707	.139	224.482
Ee	24	-	-	-	-	-
Fa	41	.052	.515	.366	.036	60.179
Fb	170	.088	.220	.805	.108	289.366
Fc	38	.026	.185	.103	.028	53.189
Fd	24	ni	ni	ni	ni	ni
Fe	32	-	-	-	-	-

[2]Blanks indicate that the least squares estimate of parameters reduced the probability law to Probability Law I; "ni" means that there is no information (results were lost).

Table C.4 Statistics pertaining to least squares parameter estimates for Probability Law V.

Data set	$n_j(0)$	β	λ_1	λ_2	S_V	$-\ln L_V$
Aa	42	.982	3.026	.013	.048	19.672
Ab	71	.869	2.134	.193	.074	66.166
Ac	57	.868	1.643	.123	.052	65.937
Ba	83	.635	2.096	.272	.022	121.815
Bb	103	.374	.526	.193	.021	249.898
Ca	130	.965	.905	.080	.018	160.690
Cb	209	.488	1.389	.256	.025	358.063
Cc	129	.385	.974	.204	.030	271.542
Da	22	.117	6.294	.487	.020	37.280
Db	97	ni	ni	ni	ni	ni
Dc	71	-	-	-	-	-
Ea	38	.587	2.030	.308	.009	40.751
Eb	18	.369	4.389	.087	.057	27.548
Ec	39	.554	.600	.133	.018	66.273
Ed	122	.373	.890	.067	.138	224.327
Ee	24	-.040	.875	.125	.048	47.411
Fa	41	.712	.708	.060	.031	59.931
Fb	170	.239	.963	.088	.107	289.095
Fc	38	.666	.282	.050	.028	53.189
Fd	24	-.221	.078	.055	.035	39.492
Fe	32	-	-	-	-	-

APPENDIX D

Observations and Predictions for Data Sheets

Table D.1 Data set Aa: MIGRATORY FARM LABORERS IN MICHIGAN (1935-1967), 9-12 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	42	0	42	42.0	42.0	42.0	42.0
0.1	42	3	39	35.1	33.1	32.8	32.5
0.2	42	14	25	29.4	26.5	26.0	25.4
0.3	42	10	15	24.6	21.4	20.8	20.0
0.4	42	3	12	20.5	17.5	16.9	15.8
0.5	42	5	7	17.2	14.4	13.9	12.7
0.6	42	1	6	14.4	12.0	11.6	10.3
1.0	42	2	4	7.0	6.2	6.1	5.2
1.1	42	1	3	5.9	5.4	5.3	4.5
2.0	42	1	2	1.2	1.7	1.9	2.0
3.3	42	1	1	0.1	0.5	0.7	1.1
4.7	42	1	0	0.0	0.2	0.3	0.6

Table D.2 Data set Ab: MIGRATORY FARM LABORERS IN MICHIGAN (1935-1967), 4-8 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	71	0	71	71.0	71.0	71.0	71.0
0.1	71	4	67	64.5	61.1	60.3	59.9
0.2	71	8	59	58.5	52.9	51.8	50.9
0.3	71	13	46	53.1	46.2	44.9	43.6
0.4	71	7	39	48.2	40.7	39.3	37.6
0.5	71	18	21	43.8	36.0	34.6	32.7
0.6	71	2	19	39.7	32.0	30.8	28.6
0.7	71	1	18	36.1	28.6	27.5	25.3
0.9	71	1	17	29.7	23.2	22.4	20.3
1.0	71	5	12	27.0	21.0	20.4	18.3
2.0	71	2	10	10.3	9.2	9.7	9.2
2.5	71	1	9	6.3	6.6	7.3	7.4
2.6	71	1	8	5.7	6.2	7.0	7.1
2.8	71	1	7	4.7	5.5	6.3	6.5
3.3	71	1	6	2.9	4.2	5.0	5.4
4.0	71	1	5	1.5	3.0	3.7	4.2
4.1	71	1	4	1.3	2.8	3.5	4.0
5.2	71	1	3	0.5	1.8	2.3	2.7
5.5	71	1	2	0.3	1.6	2.0	2.4
6.7	71	1	1	0.1	1.1	1.3	1.6
7.2	71	1	0	0.1	0.9	1.1	1.3

Table D.3 Data set Ac: MIGRATORY FARM LABORERS IN MICHIGAN (1935-1967), 0-3 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	57	0	57	57.0	57.0	57.0	57.0
0.1	57	3	54	53.7	49.9	49.9	50.3
0.2	57	5	49	50.6	44.1	43.9	44.5
0.3	57	6	43	47.7	39.4	38.9	39.4
0.4	57	9	34	44.9	35.4	34.7	35.0
0.5	57	9	25	42.3	32.0	31.1	31.2
0.6	57	3	22	39.9	29.1	28.0	27.8
0.7	57	3	19	37.5	26.6	25.4	24.9
0.8	57	1	18	35.4	24.4	23.1	22.4
1.0	57	3	15	31.4	20.8	19.4	18.3
1.1	57	1	14	29.6	19.3	17.9	16.6
1.5	57	1	13	23.3	14.8	13.4	11.8
1.8	57	1	12	19.5	12.4	11.1	9.6
1.9	57	1	11	18.4	11.7	10.5	9.0
2.0	57	4	7	17.3	11.1	10.0	8.5
2.2	57	1	6	15.3	10.1	9.0	7.7
2.3	57	1	5	14.5	9.6	8.6	7.3
6.4	57	1	4	1.3	2.6	3.2	3.6
7.4	57	1	3	0.7	2.1	2.9	3.3
8.0	57	1	2	0.5	1.9	2.7	3.1
13.8	57	1	1	0.0	0.8	1.6	1.7
20.6	57	0	1	0.0	0.4	0.8	0.9

Table D.4 Data set Ba: MIGRATORY FARM LABORERS IN TEXAS (1935-1967), PREVIOUS SEQUENCE NONAGRICULTURAL

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	83	0	83	83.0	83.0	83.0	83.0
0.2	83	16	67	74.7	67.6	67.1	66.0
0.3	83	8	59	70.9	61.5	60.9	59.4
0.4	83	3	56	67.2	56.2	55.5	53.7
0.5	83	13	43	63.8	51.6	50.8	48.9
0.6	83	8	35	60.5	47.6	46.7	44.7
0.8	83	2	33	54.4	40.9	39.9	38.1
0.9	83	2	31	51.6	38.0	37.1	35.4
1.0	83	4	27	49.0	35.5	34.6	33.1
1.1	83	1	26	46.5	33.2	32.4	31.0
1.2	83	1	25	44.1	31.2	30.4	29.2
1.4	83	1	24	39.7	27.6	27.0	26.3
2.0	83	3	21	28.9	20.0	19.9	20.4
2.2	83	1	20	26.0	18.2	18.3	19.1
2.6	83	1	19	21.1	15.3	15.6	16.9
3.0	83	4	15	17.1	13.0	13.6	15.1
3.1	83	2	13	16.2	12.5	13.2	14.7
3.2	83	1	12	15.4	12.1	12.8	14.3
3.6	83	1	11	12.4	10.5	11.3	13.0
4.0	83	1	10	10.1	9.2	10.2	11.7
4.4	83	1	9	8.2	8.2	9.2	10.7
4.9	83	1	8	6.3	7.1	8.2	9.4
5.0	83	1	7	5.9	6.9	8.0	9.2
5.1	83	1	6	5.6	6.7	7.8	9.0
5.3	83	1	5	5.1	6.4	7.5	8.6
6.5	83	1	4	2.7	4.8	5.8	6.4
11.2	83	1	3	0.2	2.1	2.3	2.1
13.0	83	1	2	0.1	1.7	1.7	1.4
16.0	83	1	1	0.0	1.2	0.9	0.7
17.0	83	1	0	0.0	1.1	0.8	0.5

Table D.5 Data set Bb: MIGRATORY FARM LABORERS IN TEXAS (1935-1967), PREVIOUS SEQUENCE NOT NONAGRICULTURAL

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	103	0	103	103.0	103.0	103.0	103.0
0.1	103	2	101	100.6	100.2	100.1	100.2
0.2	103	3	98	98.2	97.5	97.3	97.4
0.3	103	3	95	95.9	94.9	94.7	94.7
0.4	103	1	94	93.6	92.3	92.1	92.1
0.5	103	4	90	91.4	89.9	89.5	89.6
0.6	103	2	88	89.3	87.5	87.1	87.2
0.7	103	1	87	87.2	85.1	84.8	84.9
0.8	103	1	86	85.1	82.9	82.5	82.6
1.0	103	14	72	81.1	78.6	78.1	78.2
1.1	103	1	71	79.2	76.5	76.1	76.1
1.2	103	1	70	77.4	74.5	74.0	74.1
1.3	103	2	68	75.5	72.6	72.1	72.2
1.5	103	1	67	72.0	68.9	68.4	68.4
2.0	103	12	55	63.9	60.5	60.1	60.0
2.1	103	1	54	62.4	59.0	58.5	58.5
2.2	103	3	51	60.9	57.5	57.1	57.0
2.3	103	2	49	59.5	56.1	55.6	55.6
2.5	103	2	47	56.7	53.3	52.9	52.8
3.0	103	1	46	50.4	47.0	46.7	46.6
3.1	103	1	45	49.2	45.9	45.6	45.4
3.3	103	2	43	46.9	43.7	43.4	43.2
4.0	103	4	39	39.7	36.9	36.7	36.5
4.1	103	3	36	38.7	36.0	35.9	35.6
4.2	103	1	35	37.8	35.1	35.1	34.8
4.4	103	1	34	36.1	33.5	33.5	33.2
4.5	103	2	32	35.2	32.7	32.7	32.4
5.0	103	3	29	31.3	29.1	29.2	28.9
5.1	103	2	27	30.5	28.5	28.5	28.2
5.2	103	2	25	29.8	27.8	27.9	27.6
5.3	103	1	24	29.1	27.2	27.3	27.0
5.5	103	2	22	27.7	26.0	26.1	25.8
6.0	103	3	19	24.6	23.2	23.3	23.1
6.6	103	1	18	21.3	20.3	20.5	20.3
8.0	103	4	14	15.3	15.0	15.3	15.1
8.2	103	1	13	14.6	14.3	14.7	14.5
9.0	103	1	12	12.0	12.1	12.5	12.4
9.3	103	1	11	11.2	11.4	11.7	11.7

Table D.5 (cont'd.) MIGRATORY FARM LABORERS IN TEXAS (1935-1967), PREVIOUS SEQUENCE NOT NONAGRICULTURAL

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
10.4	103	1	10	8.6	9.2	9.5	9.4
10.5	103	1	9	8.4	9.0	9.3	9.3
11.0	103	1	8	7.5	8.1	8.4	8.4
11.1	103	1	7	7.3	8.0	8.3	8.3
11.6	103	1	6	6.5	7.2	7.5	7.6
14.0	103	1	5	3.7	4.6	4.8	4.9
16.2	103	1	4	2.2	3.1	3.3	3.4
17.2	103	1	3	1.7	2.7	2.7	2.8
19.1	103	2	1	1.1	1.9	2.0	2.1
28.5	103	1	0	0.1	0.5	0.4	0.4

Table D.6 Data set Ca: NONFARM LABORERS IN MICHIGAN AND TEXAS (1935-1967), 9-12 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	130	0	130	130.0	130.0	130.0	130.0
0.1	130	11	119	121.3	118.9	118.9	119.1
0.2	129	12	106	112.3	108.2	108.1	108.4
0.3	129	9	97	104.7	99.3	99.2	99.4
0.4	129	6	91	97.7	91.4	91.2	91.3
0.5	128	7	83	90.5	83.6	83.3	83.2
0.6	127	6	76	83.7	76.6	76.2	75.9
0.7	127	5	71	78.1	70.9	70.4	69.9
0.8	127	4	67	72.9	65.7	65.1	64.4
0.9	127	1	66	68.0	60.9	60.4	59.4
1.0	127	15	51	63.4	56.6	56.0	54.9
1.1	127	8	43	59.2	52.7	52.0	50.7
1.2	127	3	40	55.2	49.1	48.4	46.9
1.3	127	1	39	51.5	45.8	45.1	43.5
1.5	127	2	37	44.8	40.0	39.3	37.5
1.6	127	1	36	41.8	37.5	36.8	34.9
1.7	127	1	35	39.0	35.1	34.4	32.5
1.8	127	1	34	36.4	33.0	32.3	30.3
2.0	127	11	23	31.7	29.2	28.5	26.5
2.1	127	2	21	29.6	27.5	26.8	24.8
2.2	127	3	18	27.6	25.9	25.2	23.3
2.3	127	1	17	25.7	24.4	23.8	21.9
2.5	127	1	16	22.4	21.8	21.2	19.4
2.7	126	1	14	19.3	19.3	18.9	17.2
2.9	125	1	12	16.7	17.2	16.8	15.4
3.0	125	3	9	15.6	16.3	16.0	14.6
3.1	125	1	8	14.5	15.5	15.2	13.9
4.0	125	1	7	7.8	10.0	10.0	9.6
4.5	125	0	7	5.5	8.0	8.2	8.2
5.4	124	0	6	2.9	5.5	5.8	6.4
6.2	123	0	5	1.7	4.0	4.5	5.4
7.1	122	1	3	0.9	2.9	3.5	4.6
7.7	122	1	2	0.6	2.4	3.0	4.1
8.8	122	0	2	0.3	1.7	2.4	3.4
9.0	121	1	0	0.2	1.6	2.2	3.3

Table D.7 Data set Cb: NONFARM LABORERS IN MICHIGAN AND TEXAS (1935-1967), 4-8 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	209	0	209	209.0	209.0	209.0	209.0
0.1	209	12	197	200.9	195.5	195.5	195.5
0.2	209	15	182	193.1	183.4	183.2	183.2
0.3	208	4	177	184.8	171.5	171.2	171.1
0.4	207	9	167	176.8	160.7	160.2	160.1
0.5	207	30	137	169.9	151.5	151.0	150.7
0.6	206	9	127	162.6	142.5	141.8	141.4
0.7	205	2	124	155.5	134.2	133.5	132.8
0.8	204	5	118	148.8	126.5	125.8	125.0
0.9	204	1	117	143.0	120.1	119.3	118.4
1.0	204	22	95	137.5	114.1	113.3	112.3
1.1	203	4	90	131.5	108.1	107.2	106.1
1.2	203	3	87	126.4	103.0	102.1	101.0
1.5	203	4	83	112.3	89.7	88.9	87.7
1.6	203	1	82	108.0	85.8	85.1	83.9
1.7	203	0	82	103.8	82.2	81.5	80.4
1.8	202	1	80	99.3	78.5	77.8	76.7
1.9	202	1	79	95.4	75.3	74.7	73.7
2.0	202	9	70	91.7	72.3	71.8	70.9
2.1	202	4	66	88.2	69.5	69.0	68.2
2.2	202	5	61	84.8	66.9	66.5	65.7
2.5	202	1	60	75.3	59.8	59.6	59.2
2.6	202	2	58	72.4	57.7	57.6	57.3
2.7	202	2	56	69.6	55.7	55.7	55.5
3.0	202	7	49	61.8	50.3	50.5	50.7
3.1	201	1	47	59.1	48.4	48.7	49.0
3.2	201	2	45	56.8	46.9	47.2	47.6
3.3	201	4	41	54.6	45.4	45.8	46.3
3.5	201	2	39	50.5	42.7	43.2	43.9
3.7	201	1	38	46.7	40.2	40.9	41.7
4.0	201	5	33	41.4	36.9	37.7	38.7
5.0	201	2	31	27.9	28.3	29.5	30.9
5.1	201	1	30	26.9	27.6	28.8	30.2
5.3	201	2	28	24.8	26.3	27.6	29.0
5.5	201	0	28	22.9	25.1	26.4	27.8
6.0	200	2	25	18.7	22.3	23.6	25.0
6.1	200	2	23	18.0	21.8	23.1	24.5
6.2	200	1	22	17.3	21.4	22.7	24.0

Table D.7 (cont'd.) NONFARM LABORERS IN MICHIGAN AND TEXAS (1935-1967), 4-8 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
6.5	200	2	20	15.4	20.1	21.4	22.6
6.7	200	0	20	14.2	19.3	20.5	21.8
7.0	199	2	17	12.6	18.0	19.3	20.4
7.1	199	1	16	12.1	17.7	18.9	20.0
7.3	199	1	15	11.2	17.0	18.2	19.3
7.4	199	1	14	10.7	16.7	17.9	18.9
7.5	199	1	13	10.3	16.4	17.6	18.5
7.7	199	1	12	9.5	15.8	17.0	17.8
9.0	199	3	9	5.7	12.6	13.5	13.9
9.5	199	0	9	4.7	11.6	12.4	12.6
10.0	198	1	7	3.8	10.7	11.3	11.4
10.5	198	0	7	3.1	10.0	10.4	10.4
11.0	197	1	5	2.6	9.2	9.5	9.4
11.9	197	0	5	1.8	8.2	8.2	7.9
12.0	196	1	3	1.7	8.0	8.1	7.7
15.8	196	0	3	0.4	5.1	4.4	3.8
18.3	195	0	2	0.1	4.0	2.9	2.3
23.3	194	1	0	0.0	2.6	1.3	0.9

Table D.8 Data set Cc: NONFARM LABORERS IN MICHIGAN AND TEXAS (1935-1967), 0-3 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	129	0	129	129.0	129.0	129.0	129.0
0.1	129	3	126	125.6	123.8	123.5	123.7
0.2	129	8	118	122.2	118.9	118.3	118.7
0.3	129	3	115	119.0	114.3	113.4	114.0
0.4	129	6	109	115.8	109.9	108.9	109.5
0.5	129	12	97	112.8	105.8	104.6	105.3
0.6	129	3	94	109.8	101.9	100.6	101.3
0.7	129	3	91	106.9	98.2	96.8	97.5
0.8	129	1	90	104.0	94.7	93.3	93.9
0.9	129	1	89	101.3	91.3	89.9	90.5
1.0	129	9	80	98.6	88.1	86.7	87.3
1.1	128	5	74	95.2	84.5	83.1	83.6
1.2	128	1	73	92.7	81.6	80.3	80.7
1.8	128	3	70	78.9	67.1	66.2	66.2
1.9	128	1	69	76.8	65.1	64.2	64.1
2.0	128	7	62	74.8	63.1	62.3	62.2
2.2	127	5	56	70.3	59.0	58.4	58.1
2.3	127	1	55	68.4	57.3	56.8	56.5
2.7	127	1	54	61.5	51.1	51.0	50.5
2.9	127	2	52	58.2	48.4	48.4	47.9
3.0	126	10	41	56.3	46.7	46.8	46.3
3.3	126	1	40	51.9	43.2	43.5	43.0
3.8	126	1	39	45.4	38.1	38.8	38.2
3.9	126	0	39	44.2	37.1	37.9	37.3
4.0	125	4	34	42.7	36.0	36.8	36.2
4.1	125	1	33	41.5	35.1	36.0	35.4
4.2	125	2	31	40.4	34.3	35.2	34.7
4.3	125	1	30	39.3	33.5	34.5	34.0
4.4	125	1	29	38.3	32.7	33.8	33.3
4.6	125	1	28	36.3	31.3	32.4	31.9
4.7	125	1	27	35.3	30.6	31.7	31.3
4.8	125	1	26	34.4	29.9	31.1	30.6
5.0	125	1	25	32.6	28.6	29.9	29.5
5.1	125	1	24	31.7	28.0	29.3	28.9
6.0	125	1	23	24.9	23.3	24.7	24.5
6.2	125	1	22	23.6	22.4	23.8	23.6
6.4	125	1	21	22.4	21.5	23.0	22.8
6.5	125	0	21	21.8	21.1	22.6	22.4

Table D.8 Data set Cc: NONFARM LABORERS IN MICHIGAN AND TEXAS (1935-1967), 0-3 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	129	0	129	129.0	129.0	129.0	129.0
0.1	129	3	126	125.6	123.8	123.5	123.7
0.2	129	8	118	122.2	118.9	118.3	118.7
0.3	129	3	115	119.0	114.3	113.4	114.0
0.4	129	6	109	115.8	109.9	108.9	109.5
0.5	129	12	97	112.8	105.8	104.6	105.3
0.6	129	3	94	109.8	101.9	100.6	101.3
0.7	129	3	91	106.9	98.2	96.8	97.5
0.8	129	1	90	104.0	94.7	93.3	93.9
0.9	129	1	89	101.3	91.3	89.9	90.5
1.0	129	9	80	98.6	88.1	86.7	87.3
1.1	128	5	74	95.2	84.5	83.1	83.6
1.2	128	1	73	92.7	81.6	80.3	80.7
1.8	128	3	70	78.9	67.1	66.2	66.2
1.9	128	1	69	76.8	65.1	64.2	64.1
2.0	128	7	62	74.8	63.1	62.3	62.2
2.2	127	5	56	70.3	59.0	58.4	58.1
2.3	127	1	55	68.4	57.3	56.8	56.5
2.7	127	1	54	61.5	51.1	51.0	50.5
2.9	127	2	52	58.2	48.4	48.4	47.9
3.0	126	10	41	56.3	46.7	46.8	46.3
3.3	126	1	40	51.9	43.2	43.5	43.0
3.8	126	1	39	45.4	38.1	38.8	38.2
3.9	126	0	39	44.2	37.1	37.9	37.3
4.0	125	4	34	42.7	36.0	36.8	36.2
4.1	125	1	33	41.5	35.1	36.0	35.4
4.2	125	2	31	40.4	34.3	35.2	34.7
4.3	125	1	30	39.3	33.5	34.5	34.0
4.4	125	1	29	38.3	32.7	33.8	33.3
4.6	125	1	28	36.3	31.3	32.4	31.9
4.7	125	1	27	35.3	30.6	31.7	31.3
4.8	125	1	26	34.4	29.9	31.1	30.6
5.0	125	1	25	32.6	28.6	29.9	29.5
5.1	125	1	24	31.7	28.0	29.3	28.9
6.0	125	1	23	24.9	23.3	24.7	24.5
6.2	125	1	22	23.6	22.4	23.8	23.6
6.4	125	1	21	22.4	21.5	23.0	22.8
6.5	125	0	21	21.8	21.1	22.6	22.4

Table D.8 (cont'd.) NONFARM LABORERS IN MICHIGAN AND TEXAS (1935-1967), 0-3 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
7.0	124	2	18	18.9	19.1	20.6	20.4
7.1	124	1	17	18.4	18.8	20.2	20.1
7.3	124	1	16	17.4	18.1	19.5	19.5
8.1	124	1	15	14.1	15.8	17.1	17.1
9.3	124	0	15	10.2	13.0	14.1	14.2
10.0	123	3	11	8.4	11.6	12.5	12.6
10.7	123	0	11	6.9	10.5	11.2	11.4
12.0	122	1	9	4.8	8.7	9.1	9.3
13.0	122	1	8	3.7	7.7	7.9	8.0
13.6	122	0	8	3.2	7.2	7.2	7.3
13.8	121	1	6	3.0	6.9	6.9	7.0
14.0	121	3	3	2.8	6.8	6.7	6.8
15.0	121	1	2	2.1	6.0	5.8	5.9
18.3	121	1	1	0.9	4.3	3.6	3.6
23.2	121	0	1	0.2	2.8	1.7	1.7

Table D.9 Data set Da: NONMIGRATORY FARM LABORERS IN MICHIGAN AND TEXAS (1935-1967), 9-12 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	22	0	22	22.0	22.0	22.0	22.0
0.2	22	3	19	20.2	19.5	19.5	19.6
0.3	22	2	17	19.3	18.5	18.4	18.5
0.4	22	1	16	18.5	17.4	17.4	17.5
0.5	22	2	14	17.7	16.5	16.4	16.6
0.9	22	0	14	14.9	13.4	13.3	13.4
1.0	21	1	12	13.6	12.1	12.1	12.1
1.1	21	2	10	13.0	11.6	11.5	11.6
1.6	21	1	9	10.4	9.1	9.1	9.1
2.0	21	2	7	8.8	7.7	7.7	7.6
2.3	21	1	6	7.7	6.8	6.8	6.7
2.5	21	1	5	7.0	6.3	6.3	6.2
4.0	21	3	2	3.7	3.6	3.7	3.6
8.2	21	0	2	0.6	1.2	1.2	1.2
8.5	20	1	0	0.5	1.1	1.0	1.1

Table D.10 Data set Db: NONMIGRATORY FARM LABORERS IN MICHIGAN AND TEXAS (1935-1967), 4-8 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	97	0	97	97.0	97.0	97.0	97.0
0.2	97	3	94	91.4	91.2	91.2	91.2
0.3	97	1	93	88.7	88.5	88.5	88.4
0.5	97	8	85	83.5	83.2	83.2	83.1
0.6	97	1	84	81.1	80.7	80.7	80.6
0.7	96	3	80	77.8	77.5	77.5	77.4
0.9	95	1	78	72.6	72.1	72.1	72.0
1.0	95	12	66	70.4	70.0	69.9	69.8
1.1	94	4	61	67.6	67.2	67.1	67.0
1.5	94	2	59	60.0	59.5	59.5	59.3
1.8	94	0	59	54.8	54.3	54.3	54.2
1.9	93	2	56	52.7	52.1	52.1	52.0
2.0	93	9	47	51.1	50.6	50.6	50.4
2.1	91	5	40	48.5	48.0	48.0	47.9
2.2	91	4	36	47.1	46.6	46.6	46.5
2.5	91	1	35	43.1	42.6	42.6	42.4
2.6	91	1	34	41.8	41.3	41.3	41.2
2.9	91	1	33	38.2	37.8	37.8	37.6
3.0	91	5	28	37.1	36.6	36.6	36.5
3.1	91	1	27	36.0	35.6	35.6	35.4
3.5	91	0	27	31.9	31.6	31.6	31.5
4.0	90	2	24	27.2	26.9	26.9	26.8
4.1	90	1	23	26.4	26.1	26.1	26.0
4.3	90	2	21	24.8	24.6	24.6	24.5
5.0	90	3	18	20.1	20.0	20.0	20.0
5.1	90	1	17	19.5	19.4	19.4	19.4
5.2	90	1	16	19.0	18.9	18.9	18.8
6.2	90	0	16	14.1	14.1	14.1	14.1
6.4	88	1	13	13.0	13.0	13.0	13.0
6.5	88	1	12	12.6	12.6	12.6	12.6
7.0	88	4	8	10.8	10.9	10.9	10.9
7.1	88	0	8	10.5	10.6	10.6	10.6
7.3	87	1	6	9.8	9.9	9.9	9.9
8.0	87	2	4	7.9	8.1	8.1	8.1
10.2	87	1	3	4.1	4.3	4.3	4.4
12.2	87	1	2	2.3	2.5	2.5	2.5
14.0	87	1	1	1.3	1.5	1.5	1.6
17.8	87	1	0	0.4	0.5	0.5	0.6

Table D.11 Data set Dc: NONMIGRATORY FARM LABORERS IN MICHIGAN AND TEXAS (1935-1967), 0-3 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	71	0	71	71.0	71.0	71.0	71.0
0.3	71	1	70	66.8	66.8	66.8	66.8
0.5	71	3	67	64.2	64.2	64.2	64.2
0.7	71	2	65	61.6	61.6	61.6	61.6
0.9	71	1	64	59.2	59.2	59.2	59.2
1.0	70	7	56	57.2	57.2	57.2	57.2
1.1	70	2	54	56.0	56.0	56.0	56.0
1.5	69	1	52	50.9	50.9	50.9	50.9
1.7	69	1	51	48.9	48.9	48.9	48.9
1.8	69	1	50	47.9	47.9	47.9	47.9
2.0	69	3	47	46.0	46.0	46.0	46.0
2.2	69	2	45	44.2	44.2	44.2	44.2
2.4	69	2	43	42.4	42.4	42.4	42.4
2.5	69	1	42	41.6	41.6	41.6	41.6
3.0	69	7	35	37.6	37.6	37.6	37.6
3.1	69	3	32	36.8	36.8	36.8	36.8
3.3	69	3	29	35.3	35.3	35.3	35.3
4.0	69	1	28	30.7	30.7	30.7	30.7
4.1	69	1	27	30.1	30.1	30.1	30.1
4.2	69	1	26	29.5	29.5	29.5	29.5
5.0	69	2	24	25.0	25.0	25.0	25.0
5.2	69	1	23	24.0	24.0	24.0	24.0
5.3	69	1	22	23.6	23.6	23.6	23.6
5.9	69	1	21	20.9	20.9	20.9	20.9
6.0	69	3	18	20.4	20.4	20.4	20.4
7.0	69	6	12	16.7	16.7	16.7	16.7
7.1	69	0	12	16.4	16.4	16.4	16.4
7.4	68	1	10	15.2	15.2	15.2	15.2
8.0	68	2	8	13.4	13.4	13.4	13.4
9.4	68	0	8	10.1	10.1	10.1	10.1
10.8	67	1	6	7.5	7.5	7.5	7.5
11.9	67	1	5	6.0	6.0	6.0	6.0
13.2	67	0	5	4.6	4.6	4.6	4.6
16.0	66	1	3	2.6	2.6	2.6	2.6
17.0	66	1	2	2.1	2.1	2.1	2.1
17.9	66	1	1	1.8	1.8	1.8	1.8
22.0	66	1	0	0.8	0.8	0.8	0.8

Table D.12 Data set Ea: OPERATIVES IN FABRICATED METAL MANUFACTURE IN MICHIGAN (1945-1967), REARED IN MICHIGAN, 9-12 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	38	0	38	38.0	38.0	38.0	38.0
0.1	38	3	35	35.9	33.9	33.9	34.4
0.2	37	5	29	33.1	29.8	29.7	30.4
0.3	37	2	27	31.2	27.1	26.8	27.6
0.4	37	3	24	29.5	24.9	24.5	25.2
0.5	37	3	21	27.9	23.1	22.4	23.0
0.6	36	2	18	25.7	20.9	20.1	20.6
0.7	36	2	16	24.3	19.5	18.6	19.0
0.8	36	1	15	22.9	18.3	17.3	17.5
1.0	36	2	13	20.5	16.4	15.3	15.1
1.1	36	1	12	19.4	15.5	14.4	14.2
1.5	36	1	11	15.5	12.9	11.8	11.2
1.8	36	1	10	13.1	11.5	10.5	9.8
2.0	36	1	9	11.7	10.7	9.9	9.1
2.2	36	1	8	10.4	10.0	9.3	8.6
3.1	35	1	6	6.1	7.5	7.6	7.1
3.2	34	0	5	5.6	7.1	7.3	6.9
4.5	33	0	4	2.6	5.3	6.3	6.3
5.0	32	0	3	1.9	4.7	5.9	6.0
5.4	31	0	2	1.5	4.3	5.7	5.8
5.8	30	0	1	1.1	3.9	5.4	5.6

Table D.13 Data set Eb: OPERATIVES IN FABRICATED METAL MANUFACTURE IN MICHIGAN (1945-1967), REARED IN MICHIGAN, 0-8 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	18	0	18	18.0	18.0	18.0	18.0
0.1	18	1	17	17.8	16.7	16.3	16.3
0.3	16	4	11	15.4	13.3	12.4	12.3
0.4	16	0	11	15.2	12.7	11.8	11.6
0.5	15	1	9	14.0	11.4	10.5	10.3
0.8	15	1	8	13.5	10.2	9.6	9.3
3.0	15	0	8	10.0	6.9	7.7	7.5
3.2	14	0	7	9.1	6.3	7.1	6.9
6.3	13	1	5	5.6	4.6	5.5	5.4
8.8	13	0	5	4.0	4.1	4.7	4.7
12.4	12	1	3	2.3	3.3	3.5	3.5
13.5	12	0	3	2.0	3.2	3.3	3.3
14.7	11	1	1	1.5	2.8	2.8	2.8
17.1	11	1	0	1.1	2.7	2.5	2.4

Table D.14 Data set Ec: OPERATIVES IN FABRICATED METAL MANUFACTURE IN MICHIGAN (1945-1967), REARED IN TEXAS, 9-12 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	39	0	39	39.0	39.0	39.0	39.0
0.2	39	3	36	37.5	36.5	36.2	36.2
0.3	39	1	35	36.7	35.3	34.9	34.9
0.4	39	1	34	36.0	34.2	33.7	33.7
0.6	38	1	32	33.7	31.4	30.8	30.7
0.7	38	2	30	33.0	30.5	29.9	29.8
0.8	38	1	29	32.4	29.6	29.0	28.9
1.0	37	2	26	30.3	27.3	26.7	26.5
1.1	37	2	24	29.7	26.6	26.0	25.8
1.3	36	1	22	27.7	24.6	24.0	23.8
1.5	36	1	21	26.6	23.4	22.9	22.6
1.9	36	0	21	24.6	21.3	20.9	20.7
2.0	35	2	18	23.4	20.2	20.0	19.7
2.1	35	2	16	23.0	19.8	19.6	19.3
2.2	35	0	16	22.5	19.4	19.2	18.9
2.5	34	1	14	20.6	17.7	17.6	17.3
2.6	34	0	14	20.2	17.3	17.3	17.0
2.9	33	0	13	18.4	15.9	16.0	15.7
3.2	32	0	12	16.8	14.5	14.7	14.5
3.4	31	0	11	15.7	13.6	13.9	13.7
4.3	30	1	9	12.6	11.3	11.8	11.7
4.5	30	0	9	12.1	11.0	11.5	11.4
5.2	29	1	7	10.2	9.6	10.2	10.1
6.2	29	0	7	8.3	8.4	9.0	9.1
7.2	28	1	5	6.6	7.2	7.8	7.9
9.9	28	1	4	3.8	5.4	5.8	5.9
10.2	28	1	3	3.6	5.3	5.7	5.8
13.5	28	0	3	1.9	4.0	4.0	4.1
13.6	27	0	2	1.8	3.9	3.8	3.9
14.5	26	1	0	1.4	3.5	3.4	3.4

Table D.15 Data set Ed: OPERATIVES IN FABRICATED METAL MANUFACTURE IN MICHIGAN (1945-1967), REARED IN TEXAS, 0-8 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	122	0	122	122.0	122.0	122.0	122.0
0.1	122	1	121	120.9	117.6	118.1	118.4
0.2	121	5	115	118.9	112.8	113.5	114.0
0.3	120	4	110	116.9	108.5	109.2	109.9
0.4	120	3	107	115.8	105.5	106.1	106.9
0.5	120	9	98	114.8	102.7	103.2	104.0
0.7	120	2	96	112.8	97.9	97.9	98.8
0.8	120	4	92	111.8	95.8	95.6	96.4
0.9	119	0	91	109.9	93.1	92.6	93.3
1.0	118	7	83	108.0	90.5	89.8	90.4
1.1	118	0	83	107.1	88.8	87.8	88.4
1.3	117	1	81	104.3	85.0	83.6	84.0
1.5	116	0	80	101.6	81.7	79.8	80.1
1.6	115	1	78	99.8	79.7	77.8	77.9
1.7	115	1	77	99.0	78.6	76.4	76.5
1.8	115	2	75	98.1	77.5	75.2	75.2
1.9	114	0	74	96.4	75.8	73.4	73.3
2.0	112	4	68	93.9	73.5	71.0	70.9
2.2	112	0	68	92.2	71.7	69.0	68.7
2.5	110	2	64	88.2	68.1	65.2	64.7
2.6	110	0	64	87.4	67.3	64.4	63.9
3.0	109	7	56	83.6	64.1	61.1	60.4
3.1	109	1	55	82.9	63.5	60.5	59.8
3.3	108	0	54	80.7	61.7	58.8	58.0
3.4	107	0	53	79.2	60.6	57.7	57.0
3.9	106	0	52	75.1	57.6	54.9	54.1
4.0	105	3	48	73.7	56.7	53.9	53.2
4.1	105	2	46	73.1	56.2	53.6	52.8
4.2	105	0	46	72.5	55.8	53.2	52.4
4.3	104	1	44	71.1	54.9	52.3	51.6
4.8	104	1	43	68.1	53.0	50.7	50.0
5.0	104	1	42	66.9	52.3	50.2	49.5
7.1	104	1	41	55.5	46.6	45.8	45.4
8.3	104	1	40	50.0	44.2	44.1	43.9
9.0	104	1	39	47.0	43.0	43.3	43.1
10.3	104	1	38	41.9	41.0	41.9	41.7
11.5	104	1	37	37.7	39.5	40.7	40.6
12.2	104	0	37	35.4	38.7	40.0	39.9

Table D.15 (cont'd.) OPERATIVES IN FABRICATED METAL MANUFACTURE IN MICHIGAN (1945-1967), REARED IN TEXAS, 0-8 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
12.7	103	0	36	33.5	37.7	39.2	39.1
12.8	102	0	35	32.9	37.3	38.7	38.6
14.2	101	0	34	28.8	35.6	37.1	37.1
14.3	98	1	30	27.7	34.4	36.0	35.9
14.4	97	0	29	27.2	34.0	35.5	35.5
14.5	96	0	28	26.7	33.5	35.1	35.0
14.8	94	0	26	25.4	32.6	34.1	34.1
15.2	92	0	24	24.0	31.6	33.1	33.0
15.6	90	1	21	22.7	30.6	32.1	32.0
16.3	90	1	20	21.3	30.1	31.6	31.5
16.5	90	0	20	21.0	30.0	31.5	31.4
16.8	89	0	19	20.2	29.5	30.9	30.8
17.2	88	0	18	19.3	28.9	30.3	30.2
17.5	87	0	17	18.5	28.4	29.7	29.7
18.0	86	0	16	17.5	27.8	29.1	29.0
18.3	85	0	15	16.9	27.3	28.6	28.5
18.5	84	0	14	16.4	26.9	28.1	28.0
19.2	83	1	12	15.2	26.2	27.3	27.3
19.6	81	1	9	14.3	25.4	26.5	26.4
19.9	81	0	9	14.0	25.2	26.3	26.2
20.2	80	0	8	13.4	24.8	25.8	25.7
20.4	78	0	6	12.9	24.1	25.0	24.9
21.0	77	0	5	12.0	23.5	24.4	24.3
21.2	76	0	4	11.7	23.1	24.0	23.9
22.0	75	0	3	10.7	22.5	23.2	23.2
22.1	73	0	1	10.4	21.9	22.6	22.5

Table D.16 Data set Ee: OPERATIVES IN FABRICATED METAL MANUFACTURE IN MICHIGAN (1945-1967), REARED IN MEXICO, 0-12 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	24	0	24	24.0	24.0	24.0	24.0
0.5	24	2	22	22.9	22.9	22.9	22.9
1.0	23	1	20	20.9	20.9	20.9	20.9
1.5	23	0	20	20.0	20.0	20.0	20.0
1.7	22	1	18	18.7	18.7	18.7	18.7
2.5	22	0	18	17.4	17.4	17.4	17.4
3.0	21	1	16	15.8	15.8	15.8	15.8
3.3	20	1	14	14.6	14.6	14.6	14.6
3.4	20	0	14	14.5	14.5	14.5	14.5
4.0	19	2	11	13.0	13.0	13.0	13.0
4.8	19	0	11	12.1	12.1	12.1	12.1
5.0	18	1	9	11.2	11.2	11.2	11.2
6.2	18	1	8	10.0	10.0	10.0	10.0
7.0	18	1	7	9.3	9.3	9.3	9.3
9.0	18	0	7	7.7	7.7	7.7	7.7
10.5	17	1	5	6.3	6.3	6.3	6.3
13.0	17	1	4	5.0	5.0	5.0	5.0
15.0	17	0	4	4.1	4.1	4.1	4.1
16.0	16	0	3	3.5	3.5	3.5	3.5
16.5	14	1	0	2.9	2.9	2.9	2.9

Table D.16 Data set Ee: OPERATIVES IN FABRICATED METAL MANUFACTURE IN MICHIGAN (1945-1967), REARED IN MEXICO, 0-12 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	24	0	24	24.0	24.0	24.0	24.0
0.5	24	2	22	22.9	22.9	22.9	22.9
1.0	23	1	20	20.9	20.9	20.9	20.9
1.5	23	0	20	20.0	20.0	20.0	20.0
1.7	22	1	18	18.7	18.7	18.7	18.7
2.5	22	0	18	17.4	17.4	17.4	17.4
3.0	21	1	16	15.8	15.8	15.8	15.8
3.3	20	1	14	14.6	14.6	14.6	14.6
3.4	20	0	14	14.5	14.5	14.5	14.5
4.0	19	2	11	13.0	13.0	13.0	13.0
4.8	19	0	11	12.1	12.1	12.1	12.1
5.0	18	1	9	11.2	11.2	11.2	11.2
6.2	18	1	8	10.0	10.0	10.0	10.0
7.0	18	1	7	9.3	9.3	9.3	9.3
9.0	18	0	7	7.7	7.7	7.7	7.7
10.5	17	1	5	6.3	6.3	6.3	6.3
13.0	17	1	4	5.0	5.0	5.0	5.0
15.0	17	0	4	4.1	4.1	4.1	4.1
16.0	16	0	3	3.5	3.5	3.5	3.5
16.5	14	1	0	2.9	2.9	2.9	2.9

Table D.17 Data set Fa: OPERATIVES IN MOTOR VEHICLE MANUFACTURING IN MICHIGAN (1945-1967), REARED IN MICHIGAN, 0-10 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	41	0	41	41.0	41.0	41.0	41.0
0.1	41	2	39	40.3	38.5	38.8	39.0
0.2	41	4	35	39.6	36.3	36.7	37.1
0.3	41	3	32	38.9	34.5	34.9	35.3
0.6	40	0	31	36.0	29.6	29.6	30.1
0.7	39	2	28	34.5	27.9	27.7	28.1
0.9	39	1	27	33.3	26.1	25.6	25.9
1.0	39	1	26	32.7	25.3	24.7	24.9
1.1	39	2	24	32.1	24.6	23.9	24.0
1.2	38	1	22	30.8	23.3	22.5	22.6
1.3	38	0	22	30.2	22.8	21.8	21.8
1.4	37	0	21	28.9	21.6	20.6	20.5
1.5	36	3	17	27.7	20.6	19.5	19.4
1.7	36	1	16	26.7	19.7	18.5	18.3
2.0	36	3	13	25.3	18.6	17.2	16.9
2.5	35	0	12	22.6	16.6	15.2	14.7
3.0	34	0	11	20.1	15.0	13.6	13.2
3.4	33	0	10	18.2	13.8	12.6	12.1
4.1	32	1	8	15.6	12.4	11.4	11.0
5.3	32	1	7	12.6	11.1	10.4	10.2
9.9	32	0	7	5.6	8.3	9.0	9.0
12.0	31	1	5	3.8	7.4	8.4	8.4
12.4	31	0	5	3.5	7.3	8.3	8.3
14.2	30	0	4	2.5	6.6	7.8	7.8
14.9	29	0	3	2.1	6.2	7.4	7.4
16.3	28	0	2	1.6	5.8	7.0	7.0
22.5	27	0	1	0.5	4.7	6.1	6.0

Table D.18 Data set Fb: OPERATIVES IN MOTOR VEHICLE MANUFACTURING IN MICHIGAN (1945-1967), REARED IN TEXAS, 0-10 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	170	0	170	170.0	170.0	170.0	170.0
0.1	170	2	168	168.6	165.3	165.8	166.0
0.2	169	7	160	166.2	160.2	160.8	161.2
0.3	168	1	158	163.9	155.4	156.2	156.6
0.4	167	2	155	161.6	151.0	151.8	152.3
0.5	167	7	148	160.2	147.9	148.5	149.0
0.6	166	3	144	158.0	144.1	144.5	145.0
0.7	166	1	143	156.7	141.4	141.6	142.1
0.8	166	3	140	155.4	138.8	138.8	139.3
1.0	166	10	130	152.8	134.3	133.7	134.1
1.1	165	4	125	150.6	131.4	130.5	130.8
1.2	164	0	124	148.5	128.6	127.5	127.8
1.3	162	0	122	145.5	125.2	123.9	124.0
1.5	161	2	119	142.2	121.1	119.3	119.3
1.6	161	1	118	141.0	119.6	117.5	117.4
1.8	159	3	113	137.0	115.3	112.8	112.5
1.9	159	1	112	135.9	113.9	111.2	111.0
2.0	159	9	103	134.8	112.7	109.8	109.4
2.1	158	2	100	132.8	110.7	107.7	107.3
2.2	154	2	94	128.4	106.8	103.7	103.2
2.4	153	1	92	125.4	104.0	100.6	100.1
2.7	151	0	90	120.8	99.8	96.1	95.4
3.0	150	2	87	117.0	96.5	92.7	91.9
3.1	150	1	86	116.1	95.7	91.9	91.1
3.2	149	1	84	114.3	94.3	90.4	89.6
3.6	147	0	82	109.1	90.2	86.3	85.4
3.9	146	2	79	105.7	87.7	83.8	83.0
4.0	146	2	77	104.9	87.1	83.2	82.4
4.1	146	1	76	104.0	86.5	82.7	81.8
4.3	146	0	76	102.3	85.4	81.6	80.8
4.5	144	1	73	99.2	83.2	79.5	78.7
4.6	143	1	71	97.7	82.1	78.5	77.7
4.8	142	1	69	95.5	80.5	77.1	76.3
4.9	142	1	68	94.7	80.1	76.6	75.9
5.0	141	1	66	93.2	79.0	75.7	75.0
5.1	140	2	63	91.8	78.0	74.8	74.1
5.2	140	0	63	91.1	77.6	74.4	73.7
5.7	139	0	62	86.7	75.0	72.2	71.6

Table D.18 (cont'd.) OPERATIVES IN MOTOR VEHICLE MANUFACTURING IN MICHIGAN (1945-1967), REARED IN TEXAS, 0-10 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
6.3	138	1	60	81.9	72.3	69.9	69.5
6.4	138	0	60	81.3	72.0	69.7	69.2
6.7	135	0	57	77.6	69.4	67.4	67.1
7.1	134	0	56	74.5	67.7	66.0	65.8
7.3	133	1	54	72.7	66.6	65.1	64.9
8.0	133	0	54	68.6	64.8	63.8	63.7
8.2	132	1	52	67.0	63.8	63.0	62.9
8.5	132	0	52	65.3	63.1	62.5	62.5
9.4	131	0	51	60.2	60.7	60.0	60.0
9.5	130	0	50	59.2	60.0	60.2	60.2
10.0	129	1	48	56.4	58.6	59.1	59.2
10.5	129	0	48	54.1	57.7	58.5	58.6
11.1	126	1	44	50.3	55.4	56.5	56.6
11.3	126	0	44	49.5	55.0	56.3	56.4
11.5	123	1	40	47.5	53.4	54.7	54.9
12.0	121	0	38	44.8	51.8	53.4	53.5
12.2	120	1	36	43.7	51.1	52.7	52.9
12.3	119	0	35	43.0	50.6	52.2	52.3
12.9	118	0	34	40.6	49.4	51.3	51.4
13.0	117	1	32	39.9	48.8	50.7	50.8
13.2	117	0	32	39.3	48.6	50.6	50.7
13.5	116	0	31	38.0	47.8	49.9	50.0
14.0	115	0	30	36.1	46.8	49.1	49.1
14.1	113	0	28	35.2	45.9	49.1	48.2
14.2	112	0	27	34.6	45.4	47.6	47.7
14.3	109	0	24	33.4	44.1	46.3	46.3
14.4	108	0	23	32.8	43.6	45.8	45.8
14.5	107	0	22	32.2	43.1	45.3	45.3
14.8	105	0	20	30.9	42.0	44.2	44.3
15.1	104	0	19	29.8	41.3	43.6	43.6
15.3	102	0	17	28.8	40.4	42.6	42.7
15.5	101	0	16	28.0	39.8	42.1	42.1
15.9	99	0	14	26.6	38.7	41.0	41.0
16.2	98	0	13	25.7	38.0	40.4	40.4
17.3	97	0	12	23.2	36.8	39.3	39.2
18.0	95	1	9	21.4	35.6	38.1	38.0
20.0	95	0	9	18.2	34.4	37.0	36.8
21.2	94	0	8	16.3	33.4	35.9	35.7

Table D.18 (cont'd.) OPERATIVES IN MOTOR VEHICLE MANUFACTURING IN MICHIGAN (1945-1967), REARED IN TEXAS, 0-10 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
21.4	93	0	7	15.8	32.9	35.5	35.2
21.5	92	0	6	15.5	32.5	35.0	34.7
21.6	91	0	5	15.2	32.1	34.6	34.3
21.7	90	0	4	14.9	31.7	34.2	33.9
21.9	89	0	3	14.5	31.2	33.7	33.4
22.2	88	0	2	14.0	30.7	33.2	32.9
22.7	87	0	1	13.3	30.2	32.5	32.2

Table D.19 Data set Fc: OPERATIVES IN MOTOR VEHICLE MANUFACTURING IN MICHIGAN (1945-1967), REARED IN MICHIGAN, 11-12 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	38	0	38	38.0	38.0	38.0	38.0
0.1	38	1	37	37.7	37.0	37.2	37.3
0.2	38	2	35	37.3	36.1	36.5	36.7
0.3	38	2	33	37.0	35.3	35.8	36.0
1.0	38	2	31	34.7	31.1	31.7	32.1
1.1	36	0	29	32.6	29.0	29.5	29.9
1.3	34	0	27	30.2	26.7	27.1	27.4
1.5	33	2	24	28.8	25.2	25.5	25.8
1.6	33	0	24	28.6	24.9	25.1	25.5
1.9	32	0	23	27.0	23.3	23.4	23.7
2.0	31	2	20	25.9	22.3	22.4	22.6
2.2	31	0	20	25.4	21.9	21.8	22.0
2.5	30	0	19	23.9	20.6	20.4	20.5
3.1	29	1	17	21.9	18.9	18.4	18.5
3.2	28	0	16	21.0	18.1	17.6	17.7
3.8	27	0	15	19.2	16.7	16.1	16.0
4.0	26	1	13	18.1	15.8	15.2	15.1
4.8	25	1	11	16.2	14.5	13.8	13.6
5.3	24	0	10	14.9	13.5	12.8	12.6
5.9	23	0	9	13.5	12.6	11.9	11.6
6.0	22	1	7	12.8	12.0	11.3	11.1
6.4	22	0	7	12.3	11.7	11.1	10.8
8.1	21	1	5	10.1	10.4	9.9	9.6
12.4	21	0	5	6.8	9.1	9.0	8.8
15.5	20	0	4	4.9	8.1	8.4	8.2
20.3	19	0	3	3.0	7.0	7.8	7.8
21.2	18	0	2	2.6	6.6	7.4	7.3
21.3	17	0	1	2.5	6.2	7.0	6.9

Table D.20 Data set Fd: OPERATIVES IN MOTOR VEHICLE MANUFACTURING IN MICHIGAN (1945-1967), REARED IN TEXAS, 11-12 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	24	0	24	24.0	24.0	24.0	24.0
0.2	24	1	23	23.6	23.6	23.6	23.6
0.3	24	0	23	23.4	23.3	23.3	23.3
1.0	23	2	20	21.2	21.0	21.0	21.0
1.2	23	0	20	20.8	20.6	20.6	20.6
1.7	22	0	19	19.1	18.8	18.8	18.8
2.2	21	0	18	17.5	17.2	17.2	17.2
2.3	20	1	16	16.5	16.2	16.2	16.2
2.4	20	0	16	16.4	16.1	16.1	16.1
3.0	19	1	14	14.8	14.5	14.5	14.5
3.1	19	2	12	14.7	14.4	14.4	14.4
3.5	19	0	12	14.2	13.9	13.9	13.9
4.5	18	0	11	12.4	12.1	12.1	12.1
6.0	17	1	9	10.4	10.1	10.1	10.1
6.4	17	0	9	10.0	9.8	9.8	9.8
6.6	16	0	8	9.3	9.1	9.1	9.0
7.2	15	1	6	8.3	8.1	8.1	8.1
9.1	15	0	6	7.1	7.1	7.0	7.0
9.3	14	1	4	6.5	6.5	6.5	6.4
12.6	14	0	4	5.0	5.2	5.2	5.1
13.4	13	1	2	4.3	4.5	4.5	4.5
14.0	13	0	2	4.1	4.4	4.4	4.3
19.4	12	0	1	2.4	2.9	2.9	3.0

Table D.21 Data set Fe: OPERATIVES IN MOTOR VEHICLE MANUFACTURING IN MICHIGAN (1945-1967), REARED IN MEXICO, 0-12 YEARS OF COMPLETED SCHOOLING

DURATION T IN YEARS	OBSVD N(T)	OBSVD L(T)	OBSVD S(T)	P.L. I ESTD S(T)	P.L. II ESTD S(T)	P.L. IV ESTD S(T)	P.L. V ESTD S(T)
0.0	32	0	32	32.0	32.0	32.0	32.0
0.3	32	0	32	31.6	31.6	31.6	31.1
0.5	31	1	30	30.3	30.3	30.3	29.6
0.6	31	1	29	30.2	30.2	30.2	29.3
1.0	31	1	28	29.7	29.7	29.7	28.4
1.5	31	0	28	29.0	29.0	29.0	27.5
1.7	30	1	26	27.8	27.8	27.8	26.3
2.0	30	1	25	27.5	27.5	27.5	25.9
2.1	30	1	24	27.3	27.3	27.3	25.8
2.8	30	0	24	26.5	26.5	26.5	24.9
3.8	29	1	22	24.5	24.5	24.5	23.0
4.5	29	0	22	23.8	23.8	23.8	22.4
7.0	28	0	21	20.6	20.6	20.6	19.8
7.8	27	1	19	19.1	19.1	19.1	18.5
10.0	27	0	19	17.4	17.4	17.4	17.1
10.8	26	1	17	16.1	16.1	16.1	16.0
11.2	26	0	17	15.9	15.9	15.9	15.8
12.0	25	0	16	14.7	14.7	14.7	14.8
12.1	24	0	15	14.1	14.1	14.1	14.1
12.3	23	1	13	13.4	13.4	13.4	13.5
12.4	23	0	13	13.3	13.3	13.3	13.4
12.5	22	0	12	12.7	12.7	12.7	12.8
12.8	21	0	11	11.9	11.9	11.9	12.1
13.0	20	1	9	11.3	11.3	11.3	11.4
14.7	20	0	9	10.5	10.5	10.5	10.8
15.2	19	0	8	9.7	9.7	9.7	10.0
15.8	18	0	7	9.0	9.0	9.0	9.3
18.1	17	1	5	7.6	7.6	7.6	8.1
18.9	17	1	4	7.4	7.4	7.4	7.9
19.0	17	0	4	7.3	7.3	7.3	7.9
19.1	16	1	2	6.9	6.9	6.9	7.4
20.4	16	0	2	6.5	6.5	6.5	7.1
21.2	15	0	1	5.9	5.9	5.9	6.4

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