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Models and Methods

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Why Dynamic Analysis?

Sociological theories have become increasingly concerned with social change, and temporal data are becoming widely available. Yet empirical social research still addresses primarily questions about static relationships (associations among phenomena at a single time point) and focuses mainly on cross-sectional analysis. Even when time-series or panel data are analyzed, their temporal structure is often ignored—the data are treated as though they are cross-sections with some additional methodological complications involving autocorrelations. That is, the focus is on change from one equilibrium level to another, as measured, for example, by levels of variables at successive waves of a panel.

The current distribution of effort in sociology might suggest that there is no pressing need for methods for studying change. But current practice is a poor indicator of need. The paucity of dynamic analysis may reflect a lack of information about how to study change empirically as much as a lack of interest in change.

In subsequent chapters we consider models and methods for analyzing the actual time paths of change in attributes of individuals and social systems. These models and methods are useful for answering questions about the detailed structure of social change processes. Since the most convincing evidence of the value of dynamics analysis comes from research practice, subsequent chapters discuss applications in which the use of dynamic models and methods seems to have enhanced our capacity to formulate and test sociological arguments.

These applications illustrate both how to think about the study of social dynamics and how to do it.

Even though many sociologists are already convinced of the need to study social change processes, there is by no means a consensus. And those who do perceive this need do not always agree on the reasons. Because of these disagreements, this chapter discusses the value of dynamic models and methods in general terms. Naturally we hope that those who currently do not see the value in dynamic analysis will come to appreciate it. But we also hope that those who already appreciate it will acquire an expanded understanding of its value.

Since models and methods are selected partly because they mesh with theoretical concerns, we find it useful to distinguish between theories dealing with static relationships and those dealing with social change. The former attempt to describe and explain why various attributes of social actors or social systems are associated in particular ways at some moment. The latter try to describe and explain how an individual or social system changes over time.

It seems clear that explanations of social change are studied best by dynamic analysis. Section 1.1 reviews some of the theoretical emphases in sociology that seem to mandate dynamic analysis wherever possible. At first glance dynamic analysis may seem irrelevant to those interested in explaining static relationships. In Section 1.2 we challenge this view. Having stated as forcefully as we can in Sections 1.1 and 1.2 why dynamic analysis is valuable, in Section 1.3 we try to counter common objections to dynamic analysis when its intrinsic value is not disputed.

1.1 Dynamic Analysis for Studying Change

Although realism of description is one element controlling choice of models and methods, their fit to larger theoretical objectives is another. It is not surprising that the corpus of modern quantitative methodology in sociology is static—it was developed in a period in which static images of social structure dominated American sociology. However, theoretical currents have shifted toward a greater concern with processes of change. The standard static methods are ill equipped to address questions about the time-paths of change. Thus one reason for pursuing the study of dynamic models

and methods is to adapt research practices to important theoretical concerns of the discipline.

The classical sociological theorists struck a reasonable balance between problems of order and problems of change. Because these theorists wrote at a time when industrial capitalism was transforming western Europe, not surprisingly they devoted considerable attention to the forces that created industrial capitalism, to those that shaped its institutional forms (state bureaucracy, factory enterprise, and so forth), and to the effects of rapid social change on individuals. Although their attitudes toward the changes accompanying industrialization varied, most of the classic theorists placed problems of social change at center stage.

Subsequent sociological theorists, especially in the United States, tended to emphasize order and to deemphasize change. The stress on problems of order was so complete during the heyday of functionalist theory that "social change" became identified as a substantive subfield on a par with institutionally defined subfields such as political sociology, sociology of the family, and sociology of religion. That is, change was not a major focus; instead it was one possible outcome to be explained within the context of an overarching theory based on the notion of an equilibrium.

The dominance of structural-functional theory broke down during the late 1960s. Since then new theoretical perspectives have multiplied. Some new theoretical directions retain a strong emphasis on equilibrium; others emphasize disequilibrium and change.

One important development exemplifying the former is the effort to apply the framework of neoclassical price theory to a broad range of social behavior. Initial steps in this direction were made by sociologists; two important examples are Emerson's (1962) and Blau's (1964) theories of power and social exchange. Subsequent developments have seen economists applying neoclassical price theory to traditional sociological subjects, such as marriage and family life (Becker, 1981). In fact, during the 1970s convergences between sociology and microeconomics began to occur—compare the role of schooling in the status attainment model developed by Blau and Duncan (1965) and refined by Duncan, Featherman, and Duncan (1972) with Becker's (1975) theory of human capital, or Hannan, Tuma, and Groeneveld's (1978) model of marital dissolution with Becker's (1981) theory.

At first glance the development of a sociological perspective built on a synthesis of sociology and microeconomics would seem to keep the equilibrium assumption at the core of sociological theory. Within the social sciences, the faith in equilibrium analysis has been nowhere stronger than in microeconomics. The assumption that markets function efficiently, so that social systems are almost always in equilibrium, has often directed attention away from a serious interest in processes of change in the social system. Nevertheless, the interest of many sociologists and some radical economists in multiple labor markets acts as a force against this. Moreover, whatever the view of system-level change, the long-standing interest of sociologists in social mobility clearly fosters concern with change processes on the individual level. And microeconomists working within the neoclassical framework (e.g., see Ghez and Becker, 1975; Heckman and Willis, 1976; MaCurdy, 1981) have done some sophisticated research on life-cycle patterns of individual behavior.

The recent interest in the life course of individuals in general and in their careers in particular also gives hope that an infusion of microeconomic theory into the study of individual behaviors is unlikely to stress static analysis. The notion of a life course or a career suggests a focus on the dependencies among the successive states occupied by an individual. For example, an employment career is more than a list of the jobs held by an individual. It consists of the sequence and timing of the various jobs and their association with other events, such as changes in marital status and geographical residence. Thus studies of careers (or the life course) focus on the contingencies that pertain to the possible transitions in a career line. For example, sociologists and economists have begun to explore how characteristics of early employment and unemployment affect future employment (Corcoran, 1979; Panel on Youth, 1973; Spilerman, 1977). Others have investigated how changes in husbands' and wives' labor force behavior unfold over time (Tuma, Robins, and Smith-Donals, 1980). Although the rapidly proliferating research on the life course and individual careers has a variety of substantive foci, it reveals a common interest in studying individual histories.

Many contemporary sociological theories emphasizing change are not based on an equilibrium perspective at all. American sociologists' renewed attention to Marx in the late 1960s has been a major force promoting the development of theories that stress change and

its historical context. Although most Marxist and neo-Marxist sociologists are hostile to positivist research and prefer a case-oriented historical approach, standard quantitative methods have been used to address some of the issues prominent in this theoretical tradition (for some examples, see Meyer and Hannan, 1979). Some of this research is static; it concerns the *absence* of much change in capitalist social structures to date. But some emphasizes processes of societal change; for example, see Paige (1975).

Theoretical developments on social movements have also begun to emphasize dynamics. Tilly (1978) and Skocpol (1979) have been especially prominent in redirecting attention to the organizational bases of collective protest and revolution. Rejecting the assumption that collective violence occurs when social structures are falling apart, both argue that local social organization is crucial in understanding these manifestations of social unrest. Collective violence is not an aberration but a natural by-product of social organization whose forms change as the distribution of power changes. Forces that challenge and perhaps overturn the existing order can arise even when a system is apparently stable. Such shifts place theoretical emphasis squarely on dynamics. For example, a key theoretical problem is understanding how changes in the strength of contending groups, the repressive power of a state, and the nature of the relations of a state to its neighbors affect collective violence and social revolution. Understanding the timing of collective protest and its changing forms requires dynamic analysis.

The theoretical trends sketched above, along with many others concerned with change, are fairly recent. Moreover, interest in explaining how and why social actors and social systems change over time seems to be gaining momentum. What some view as disarray in contemporary sociology may partly reflect the pluralism and struggle involved in moving from questions and arguments about static relationships to the interrelated forces for change. If movement continues in this direction, as we think it will, the need for dynamic models and methods will grow.

1.2 Dynamic Analysis for Studying Static Relationships

As we mentioned at the outset, sociologists who wish to explain static relationships—associations among properties of social actors or social system at a point in time—may believe that they

can safely forego the effort of learning and applying dynamic models and methods. In this section we argue that this belief is erroneous for two main reasons.

First, explanations of static relationships almost always assume that these relationships are unchanging, but this assumption is usually implausible, as we argue below. In such situations, static analysis can be misleading. Since dynamic models have implications for relationships at a point in time, dynamic analysis is of great value to those who wish to explain static relationships but suspect that these are not in equilibrium during the period for which data are collected.

Second, dynamic analysis has several methodological advantages over cross-sectional analysis that mean this powerful analytic tool has value for studying static relationships, even if a steady state does exist. The remainder of this section is organized around a discussion of these two themes.

1.2.1 How Often Does an Equilibrium Occur?

Two types of situations must be considered. In one, the phenomena to be explained does not appear to have a nontrivial stable equilibrium, and change is continual.¹ In the other, a stable equilibrium may exist, but the fraction of time spent near it is small. Generalizing about relationships at some moment on the basis of cross-sectional analysis is apt to be very misleading in either case.

Case 1: Continual Change. As an example of the former, consider the relationship among various attributes of individuals—their family background, schooling, income, marital status, health, happiness, and so forth. Both socially and physiologically, the human individual is continually changing—first growing rapidly and expanding its many capacities and activities; then declining rather gradually until death. Norms usually specify how the social lives of individuals should change over the life course. Anthropologists (e.g., Foner and Kertzer, 1978) report that age-related rites of passage occur in almost every society they have studied. In modern industrial societies individuals move from the parental home to school to employment to retirement to death in a well known fashion, despite

¹By nontrivial we mean an equilibrium that is scientifically interesting. For example, death of a person or extinction of a species are stable but trivial equilibria.

deviations from the normative order (Hogan, 1978, 1980; Winsborough, 1978). That change is an enduring and important feature in studying characteristics of individuals is demonstrated by the almost universal finding of age as an important explanatory variable, no matter what personal characteristic or behavior is considered.

Change seems to be the rule rather than the exception for other kinds of phenomena studied by sociologists. Most businesses are organized around efforts to increase sales and profits, which indirectly lead to an expanded work force in most instances. Many churches try to win converts as well as socialize children of adult members. Cities (at least in the United States) not only actively promote growth in population size and territory but typically regard stability as a sign of incipient decay (another form of change); see Molotch (1976). Historically many states have also tried to expand in population size and territory. Modern states typically seek to increase literacy, educational levels, health, and overall economic development (Meyer, 1980). Indeed, many social organizations of all types seem organized around a program of growth and expansion, not stability. Naturally such a program is not always successful, but with such manifest goals it is advisable to be cautious about assuming that an equilibrium currently exists.

Case 2: Stability May Exist. Persistence over time does seem prevalent in some realms of social life, suggesting that a steady state is possible. For example, the culture of primitive societies is widely regarded as being intrinsically conservative, that is, designed to reproduce itself and to resist innovation. (But at least some aspects of the culture of modern societies seem far from stable.) The power and class structures of societies often seem to change relatively slowly, and it is tempting to interpret persistence as a steady state. (However, Marx's forecast of cataclysmic change for the class structure under capitalism and Pareto's notion of cyclical shifts in the composition of elites alert us to be watchful for change in these social institutions.)

In areas in which we observe considerable persistence over time, the key methodological question is, What fraction of time are the phenomena being studied very near an equilibrium? If the fraction is close to unity, then dynamic analysis is not essential. But if the fraction is small, the choice between static and dynamic analysis matters a great deal. Even sociologists who wish to address static

arguments are well advised to conduct dynamic studies and infer static relationships from them.

A system is unlikely to spend much time near an equilibrium when it confronts a volatile environment and adapts slowly to changed circumstances. Above we mentioned several aspects of the modern world that seem organized to promote change and which indeed seem to be changing rapidly. During this century the world's population has grown enormously; the speed of communication and transportation has increased substantially; and boundaries among societies that were formerly relatively isolated have been weakened. In short, not only has the pace of change quickened, but interdependencies have increased. As Simon (1978, p. 4) put it,

When the system is complex and its environment is continually changing (i.e., in the conditions under which biological and social evolution actually take place), there is no assurance that the system's momentary position will lie anywhere near a point of equilibrium, whether local or global.

By itself the observation that social phenomena change continually does not vitiate static analysis. If typical changes are either small or predictable, adaptations may occur rapidly and readily so that departures from equilibrium are brief. What matters is the *pattern* of change, especially the magnitude and regularity of change.

Large, irregular (and therefore unpredictable) changes are especially significant because an extended period of disequilibrium is likely to follow them, which limits sharply the value of static analysis. Consider, for example, the situation of positions at the bottom and top of organizational hierarchies. Those at the bottom are usually specialized to deal with small, repetitive, and predictable changes; in contrast, those at the top deal with less certain, larger, and less frequent changes (Barnard, 1938; March and Simon, 1958). Thus, static models might describe well the activities of clerical and industrial workers, but not the activities of chief executive officers and other top managers.

The speed of response of social actors and social systems also affects the value of steady-state analysis. If adjustments to changed circumstances are quick, even large disturbances may produce only short periods of disequilibrium. Although we know little

about speeds of adjustment, existing theory does give some clues about the forces that constrain responsiveness. Two broad classes of inertial forces are factors that reflect *costs of change* and those that reflect *institutional mechanisms*.

Economic theorists stress the former. One common argument is that the uncertainty associated with the potential gains from radical change seldom offset the fairly certain costs of change in terms of additional resources consumed and time spent searching for an optimum.

Sociologists tend to emphasize institutional constraints—tacit assumptions about goals, rights, and rules of action. A social structure is highly institutionalized when its its members take rules as given in formulating and making choices. Because institutionalization reduces greatly the costs of surveillance, coordination, and control of action, it can increase the efficiency of collective action. But it is a two-edged sword. When a structure is well suited to prevailing conditions, institutionalization promotes efficiency in collective activities. If conditions change, however, institutionalized structures can serve as a powerful brake on attempts at changing rules and patterns of action.

In sum, inertial forces are commonplace. Sometimes the costs of change hinder change more than institutional constraints, and at other times the opposite is true. In either case the speed of response to alterations in the social and physical environment are often slow. Consequently, it seems reasonable to think that many phenomena possessing an equilibrium are not observed near it. Then dynamic analysis is called for.

1.2.2 The Value of Dynamic Analysis in a Steady State

Although we have stressed the comparative rarity of the existence of a steady state for most phenomena studied by sociologists, surely some phenomena not only have a steady state but also are observed near it. Static and dynamic analyses are likely to agree about broad patterns in such cases, even if they differ in detail. Hence it may seem that investigators studying static relationships in a steady state certainly can afford to ignore dynamic models and methods in their empirical investigations. In this section we mention some advantages of dynamic analysis over cross-sectional analysis that apply to this situation. Of course, these apply as well to studies of change

and to studies of static relationships out of equilibrium, but we have already indicated even stronger reasons for dynamic analysis in such situations.

The first advantage of temporal analysis is that it is the only way to tell whether a steady state currently exists. There may be sound arguments why some phenomenon *should be* in equilibrium, but only an analysis of temporal data can demonstrate that there actually is stability over time. Moreover, dynamic analysis can be used to tell whether a steady state is possible, as we discuss in Chapters 11 and 14, and how rapidly a feasible steady state will be reached, as we illustrate in Chapter 10.

A second advantage is that dynamic analysis, despite its apparent complexity, can actually simplify the study of complicated problems. In at least one crucial respect the study of change is simpler than the study of relationships at a point in time. In cross-sectional data everything often seems to depend on everything else. The apparent density and complexity of webs of causal relations pose a formidable obstacle to modeling and analysis. Nonexperimental research methods are sorely taxed in such situations. Analysis of systems of simultaneous structural equations, which provide one way to represent such relationships, involves difficult statistical and methodological challenges. Dynamic models and methods are no more complex in most instances, and often they are simpler.

In Chapter 11 we illustrate this advantage in an application dealing with organizational demography. Much research has addressed the relationship of organizational size to the size of the administrative staff from a static perspective (see Scott, 1975). At a given time point it is difficult to distinguish effects of several fundamental processes, in particular, the consequences of administrative rationality for allocations of staff from the results of the political processes by which occupational groups defend and extend their domains. In Chapter 11 we examine how the sizes of various personnel components are affected by each other and by exogenous changes separately in organizations experiencing growing and declining demand for their services. We find that the process of change in the administrative staff under declining demand differs from the process under growing demand in a way that agrees with a political theory of organizational demography. Far from complicating things, the shift from cross-sectional analysis to dynamic analysis simplifies

the task of evaluating evidence in this case. We believe that this simplification is not unusual.

A third advantage of dynamic analysis is that it is more informative than cross-sectional analysis. The example in Chapter 11 mentioned above demonstrates this point because it tells about the growth and decline of personnel components under different environmental conditions, as well as about relationships at a point in time. An empirical application presented in Chapter 10 also illustrates this advantage. Economic theory clearly predicts that the probability of family heads working at any moment is lower when a guaranteed annual income is available to families with low potential income. Both cross-sectional analyses and dynamic analyses reported in Chapter 10 support this prediction; however, the dynamic analysis provides much more information than the cross-sectional analysis. In particular, it reveals that a guaranteed annual income has rather small effects on the tendency of working family heads to leave their jobs, but that it greatly retards the tendency of nonworking family heads to find employment.

Fourth, dynamic analysis expands our ability to test arguments. Since every static model is a special case of at least one dynamic model, a dynamic model is more general. A more general model not only provides a fuller explanation of a phenomenon (and is therefore a more satisfying theory) but also increases our empirical leverage. That is, dynamic models have more abundant implications that allow them to be tested in multiple ways.

For example, it has been known for over 80 years that the Pareto distribution fits well the upper tail of several empirical distributions, including the distributions of family income and the size of firms. That is, a simple static model fits both empirical distributions, which are known to have changed fairly little over time and so can be regarded as close to a steady state. Simon (1955) proved that the Pareto distribution is the steady-state of a simple birth and death process in an open system (see Chapter 4). Many consider his reformulation of this problem to be a major advance because it shows how the Pareto distribution may arise. More pertinent to our present discussion, a birth and death process has a number of other properties that can be tested directly, which means increased avenues for evaluating this argument.

Moreover, because temporal data contain more information

than does a single cross-section, standard errors of coefficients of explanatory variables tend to be smaller in dynamic analyses than in the comparable cross-sectional analysis, as our empirical example in Chapter 10 illustrates. Finally, our ability to test arguments is also greater with dynamic analysis because one can correct for various confounding influences, such as unobserved heterogeneity. We develop this point further in Chapters 6 and 13.

Fifth, new research questions are more likely to arise out of dynamic analysis than out of cross-sectional analysis. This advantage largely follows from some of the other advantages mentioned above. For example, because dynamic analysis tell more about phenomena than does cross-sectional analysis, there are more relevant features of social life about which to ask questions.

1.3 Other Obstacles to Dynamic Analysis

If analysis of time-paths of change is so important for studying both change and static relationships, why is it so rare in empirical sociology? Several obstacles to dynamic analysis are often mentioned, even by those who value it in principle.

It is sometimes said that the major obstacle to dynamic analysis is the lack of appropriate data. Whereas static analysis can be conducted on data gathered at a single moment in time, dynamic analysis demands data on the same units over time. Cross-sectional data are much more common than temporal data for several reasons. First, it is expensive to follow people over time because they migrate, change jobs, lose interest in participating in the survey, and so forth. It is much cheaper to take a single snapshot or a series of snapshots on different samples (as in the National Opinion Research Center's "General Social Survey"). Second, the length of time needed to address some research questions is so long that stable data collection procedures cannot be maintained (because of the vagaries of research funds, shifts in an investigator's research interests, instability in measures,² and so forth).

Although we grant that temporal observation plans are often more expensive than a cross-sectional plan, we doubt that lack of

²Measures can be unstable even when the same instruments are used. For example, the same questions might continue to be asked in a survey but the meaning of the terms may change.

data explains the scarcity of dynamic analysis for two reasons. First, much sociological research now uses archival data that follow actors such as organizations or countries over time. Yet dynamic analysis is scarcely more common in these fields than elsewhere in sociology. Second, the availability of data reflects at least partly the interests of social scientists. Individual researchers collect and distribute data, and social scientists advise government agencies about what sorts of data should be collected. That relatively few temporal data sets have been available in the past may have been as much a consequence as a cause of the dominance of static analysis. As we indicate in the next chapter, temporal data are becoming widely available in many fields of sociology. While data availability may once have been a major constraint on the spread of dynamic models and methods, it appears to be so no longer.

A second obstacle to empirical dynamic analysis in the eyes of some people is its complexity. Many sociologists assume that dynamic analysis is much more complex than static analysis. We do not doubt that empirical analysis of social dynamics is subtle and at times difficult. The chapters that follow discuss a number of unsolved conceptual and methodological problems. Moreover, a serious application of the dynamic models and methods we propose will surely unveil additional complications.

This does not mean, however, that meaningful static analysis is simpler. We are certainly less familiar with the empirical study of change than with the study of static relationships. But we should not confuse unfamiliarity with difficulty. It is true that a mastery of dynamic models and methods is likely to involve some new mathematics for most sociologists; however, some aspects can be learned with only small extensions of the mathematical knowledge common among sociologists currently doing quantitative empirical research. Moreover, as in learning most things, mastery is acquired gradually. Even a long road can be traversed by many small steps. This book, we hope, will help to speed sociologists' journey towards this goal.

1.4 Conclusions

If empirical research is to clarify theoretical issues, research strategies must fit substantive problems. We have argued that contemporary sociological theory has begun to explore systematic sources of change. Sociologists increasingly study phenomena that

are not in equilibrium, such as the life course of individuals, political attitudes, gender roles, class and ethnic conflict, mass political violence, evolution of organizational forms, and structural changes in national and world systems.

The static methods still dominant in sociological research are not well suited to the study of these phenomena and to the evaluation of modern and classical theories of them. As long as empirical sociological research relies solely on the familiar static methods, quantitative research will appear irrelevant to these concerns. However, by building dynamic models and estimating them with appropriate methods, we can bring quantitative methods to bear on a much broader range of problems and theories than in the past.

We also argue that dynamic analysis can be helpful in the study of static relationships—associations among attributes of social actors or social systems at a single time point. If one wishes to make generalizations about static relationships to time points other than those at which data are collected, static analysis must assume that the phenomena being explained are in equilibrium. Yet many phenomena of interest to sociologists do not seem to possess an equilibrium. Still others may have one but not spend much time near it. Dynamic analysis is clearly called for in these cases.

Dynamic analysis also has considerable value in studies of phenomena that are in equilibrium. It is the only way to tell whether or not an equilibrium currently exists. In addition, it is more informative, more powerful, more provocative, and sometimes even simpler than static analysis. Thus, whatever one wishes to explain, dynamic analysis can be beneficial.

Ample motivation for dynamic analysis exists; therefore the paucity of empirical studies of change in the sociological literature cannot be explained by its lack of worth. We think that the primary problem is methodological. The literature on methods for analyzing data on change over time is both fragmentary and disorganized, and it tends to emphasize potential pitfalls of temporal analysis (such as autocorrelation bias) rather than to emphasize its advantages. Clear guidelines concerning alternative designs, models, and estimators are lacking. This book is intended to help fill this void. Having discussed reasons for dynamic analysis, we now turn to the methodological issues that have impeded progress in studying change. We begin by surveying common approaches to the analysis of temporal data.

Varieties of Temporal Analysis: Overview and Critique

Although most sociological research in the 1960s and 1970s relied on cross-sectional analysis, the field has a long history of interest in temporal analysis. The traditional interest derives mainly from a concern that causal inferences cannot be made dependably from a cross-section because such data cannot show that one variable affects *change* in another. This concern has frequently been accompanied by exaggerated claims for the power of temporal analysis. The older literature abounds with assertions that temporal analysis is always superior to cross-sectional analysis. As we discuss at length in Chapter 13, analyses of cross-sections can give sounder results than temporal analyses when confounding influences vary more over time than over individuals. As a result of this knowledge, a much more tempered view of the methodological value of temporal analysis currently prevails in sociology.

As we noted in the previous chapter, current enthusiasm for temporal analysis stems more from substantive concerns than from methodological prejudice. Macrosociology has begun to focus on issues of structural change. Likewise, development and careers have loomed progressively larger in studies of individuals. Sociologists of many stripes have come to emphasize change, and whatever its other benefits, temporal analysis is indispensable for the study of change.

There are at least two largely separate literatures on temporal analysis, one dealing with qualitative outcomes (including both categorical and ordinal variables), the other with quantitative (i.e.,

integers, existentially, and their parts only live as *they* live. Still, in them, we can call parts, parts.—But when, without circumlocution or disguise, I thus come over to your views, I insist that those of you who applaud me (if any such there be) should recognize the obligations which the new agreement imposes on yourselves. Not till you have dropped the old phrases, so absurd or so empty, of ideas “self-compounding” or “united by a spiritual principle”; not till you have in your turn succeeded in some such long inquiry into conditions as the one I have just failed in; not till you have laid bare more of the nature of that altogether unique kind of complexity in unity which mental states involve; not till then, I say, will psychology reach any real benefit from the conciliatory spirit of which I have done what I can to set an example.

Has the day passed in American psychology when its parts are just parts, its divisions just divisions, and the search for integers has been abandoned? Is the apartness so characteristic of contemporary psychology the consequence of the apartness so many people feel in their own lives? Is there no center that can hold psychology together? Must we resign ourselves to a modern psychology that is completely a reflection of modern living? Was our fall from earthly grace signaled when psychology labeled William James and John Dewey as philosophers, *only* philosophers?

I could have served the purposes of this occasion better if I had, as I initially fantasized, read you excerpts from the writings of these two giants. I ask your pardon for uncourageously succumbing to the demand characteristic of this occasion.

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Charting the Process of Change: A Primer on Survival Analysis¹

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Survival analysis is a powerful and useful technique for understanding qualitative change. This article provides a practical, nontechnical introduction to the use of survival analysis for social scientists. Important issues in using survival analysis are discussed, including research design, data preparation and management, and data analysis. Attendance data from a self-help organization are used to illustrate common survival analysis tasks such as describing the overall survival and hazard functions, examining covariate effects, and modeling the form of the hazard function over time. An appendix that discusses the strengths and weaknesses of current survival analysis computer programs is included.

KEY WORDS: survival analysis; self-help.

It was ordained at the beginning of the world that certain signs should prefigure certain events.

—Cicero, *De Divinatione*

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The measurement of change is a fundamental task for social researchers. The etiology of a psychological disorder, the length of time it takes for a preventive intervention to take effect, how long those effects last, period of time until a battered spouse seeks legal intervention, the course a self-help group takes from birth to death, prediction of when a person may become violent—these are all examples of common social and psychological research questions that cannot be understood without measuring and understanding change.

Although many psychological theories define change as a series of incremental shifts in some variable that can be measured quantitatively, much, if not most change is actually qualitative in nature (Widaman, 1991). Change is seen as an event that marks the shift from one state to another; it is transformational rather than incremental. This viewpoint of change as transformation can be seen explicitly in applied psychological work on change in organizations (Quinn & Cameron, 1988), the life-cycles of behavior settings (Wicker & King, 1988), transformational processes in person-environment relations (Stokols, 1988), and in the more applied side of developmental psychology (Sroufe & Jacobvitz, 1989).

The purpose of this paper is to provide a practical introduction to survival analysis, one of the most useful statistical techniques for analyzing qualitative change. Despite its fundamental importance, change remains a neglected concept in psychology (Katz, 1980). This may be due in part to the conceptual, empirical, and statistical problems inherent in the measurement of change (Cronbach & Furby, 1970; Willett, 1987). However, it may also be due to researchers' reliance on a small set of established statistical tools, and an unfamiliarity with newer techniques designed to assess change (Collins, 1991). We are all familiar with the "Rule of the Hammer," and we know it is a mistake to define our basic theories based on the limitations of our instruments. Thus, this paper is an attempt to provide information about a relatively new tool that allows a more flexible approach to understanding change.

As the title suggests, this paper is designed to help get the interested reader up to speed as quickly as possible on how to use survival analytic techniques. There are already a number of good statistical treatments of survival analysis for those who want a more in-depth or technical understanding (Allison, 1984; Blossfeld, Hamerle, & Mayer, 1989; Kalbfleisch & Prentice, 1980; Lawless, 1982; Yamaguchi, 1991). However, most of these articles assume a high level of statistical expertise, and few if any provide enough practical information about how to design survival analysis studies, collect the data, and use available software to perform

the analyses.³ For this reason, I spend most of my time in this paper introducing the techniques of survival analysis in a nontechnical manner, using real data to provide numerous grounded examples. Many advanced issues will be treated cursorily; wherever possible I refer the reader to more in-depth literature discussing these topics.

I begin by briefly defining important survival analysis terms, providing some historical background, and showing how survival analysis is relevant to many common research situations. Also, I describe a study that provides the data for the survival analysis examples appearing throughout the paper. The main section of the paper provides a detailed description with examples of how survival analysis might be used by the typical researcher. Advanced and more technical topics are then briefly covered. Finally, the paper includes an appendix that discusses computer programs that are available for survival analysis.

DEFINITION AND BACKGROUND

Survival analysis is a family of techniques that is concerned with the examination of the form and determinants of qualitative change.⁴ More specifically, the focus of survival analysis is the exploration of the timing of events and the covariates which may be related to that timing. An event is defined as a shift from one mutually exclusive state to another, occurring at a specific and known point in time.

Before the advent of survival analysis, statistical treatment of event data was problematic. Consider a hypothetical example of a study comparing the recidivism rates of drug addicts who have attended a new type of treatment program with those who have received traditional treatment. Study participants are followed for 2 years. After 2 years a certain percentage of each group will have relapsed, while the rest are still clean at the

³The recent work of Singer, Willett, and their colleagues comes closest to providing nontechnical treatment of survival analysis (Singer & Willett, 1991; Willett & Singer, 1991a), although at a more advanced level than that of this paper. In particular, their use of survival techniques to examine the careers of teachers is exemplary (Murnane, Singer, & Willett, 1988; Murnane, Singer, Willett, Kemple, & Olsen, 1991; Willett & Singer, 1991b). They are able to show the strengths of survival analysis, especially when applied to a rich longitudinal data set.

⁴Survival analysis is also sometimes referred to in the literature as event history analysis and, less frequently, failure-time analysis. Although event history analysis is somewhat more descriptive of the techniques as they are currently used, the more common and historically rooted term is used throughout the paper.

end of the study. What is the most effective way to summarize the results to illustrate the effect of the treatment program on recidivism rates? Traditional methods would report either the percentage of each group that had relapsed during the study period, or the average time until relapse for each group. There are serious problems with each of these methods. In the former case, the proportion of the group relapsing is reported, totally ignoring the timing of the relapses. For example, each group could have a 50% relapse rate, but the control group might relapse on average 3 months sooner than the experimental group. Presenting the average time until relapse, on the other hand, has the opposite problem; it takes timing information into account, but does not indicate how much of the group has relapsed during the study.

Although both pieces of information could be presented, this would still not avoid the major problem of these methods. Both the percentage of persons relapsing and mean time to relapse are statistics that are heavily dependent on the time frame of the study. A longer period of observation almost always results in larger response proportions and higher average response times. Thus, the traditional ways of summarizing event data are dependent on the arbitrarily determined study length (Lavori, Keller, & Klerman, 1984; Singer & Willett, 1991).

Another way to restate this problem is to ask how one should handle those participants who have not relapsed by the end of the study. Every study has an endpoint that is usually arbitrary with respect to the event of interest. Therefore, there are almost always cases for which the event of interest has not occurred by the time that data collection has ended. This is one example of what is known as censored data, which is discussed below in more detail. One way to handle this problem is to count these cases as missing data. However, not only is this wasteful of participants (which is something no researcher ever wants to be!) but it results in biased estimates of average survival times. Those people with long survival times are the most likely to be censored; thus, estimates of average survival times are biased downwards if censored data are dropped. Another potential solution is to assume that the event occurs at the point of censoring. So, for the above example, everyone who has not relapsed is set as relapsing at the end of the study. Although this does not result in lost subjects, it clearly biases the survival information. Although some of the censored participants would probably relapse soon after the study is ended, many may not. Their survival time is surely longer than the length of the study, but there is not a good way to estimate that time using traditional methods.

Note that lengthening the observation period of the study (even if economically feasible) does not usually eliminate the problem of censored data. Some people may never exhibit the event of interest, for example,

many drug addicts may be able to quit "cold turkey" and never again use drugs. Also, in many naturalistic nonexperimental studies participants may enter the study at various time points. Those persons who enter near the end of the study and thus have less time to have the event occur are much more likely to be censored. So although the observation period of the study may affect the problem of censored data, altering the observation period will not be able to avoid the problem. We are still left with the need for statistical techniques that can handle censored data in an efficient and unbiased manner.

One of the major strengths of survival analysis is its ability to deal with this problem of censored data. Survival analysis can handle event data without the data loss or biasing that is so problematic with other methods. Also, survival analysis can be used on many types of data from a variety of sources including prospective, retrospective, archival, and cross-sectional data (Adler & Kandel, 1983; Singer & Willett, 1991), in addition to being applicable for meta-analytic summaries of cross-study event data (Isager, Brinch, Kreiner, & Tolstrup, 1985; Lavori et al., 1984; Setze & Bond, 1985). Moreover, survival analysis lends itself to visual displays of group and subgroup survival patterns, allowing a much quicker and more intuitive understanding of the event data than quantitative summaries of event statistics. Finally, modern survival techniques offer sophisticated ways to analyze the effects of covariates on survival proportions and probabilities. For all of these reasons, survival analysis is becoming one of the most powerful tools for the analysis of change.

Modern survival analytic methods were first developed by biostatisticians interested in modeling the length of time to death of human or other living organisms (hence the term survival analysis) and engineers studying the length of time to failure of machine components (Breslow, 1974; Cox, 1972; Gail, Santner, & Brown, 1980; Kalbfleisch & Prentice, 1980; Lawless, 1982). This work in turn was partially based on the life table which is a method of summarizing event data used by actuaries and demographers since the 18th century (Pollard, Yusuf, & Pollard, 1981). More recently, survival methods have been extended to handle special cases of repeatable events and multiple types of events by sociologists studying social transitions (Blossfeld et al., 1989; Tuma & Hannan, 1984).

Although survival methods have been around for the last two decades, their use by social scientists has been sporadic. Their use seems to have caught on for only three particular research areas. First, psychiatrists have used the methods extensively to study relapse rates of persons with a variety of psychiatric conditions including anorexia nervosa (Isager et al., 1985), affective disorders (Greenhouse, Kupfer, Frank, Jarrett, & Rejman, 1987; Lavori, et al., 1984; McLeod, Kessler, & Landis, 1992), alcoholism (Hser,

Anglin, & Liu, 1991; Poikolainen, 1983), suicide (Leon, Friedman, Sweeney, Brown, & Mann, 1990), and schizophrenia (Matthews, Roper, Mosher, & Menn, 1979). Second, organizational and educational psychologists have used survival analysis in more technically sophisticated ways to examine attendance and turnover in schools and at the workplace (Fichman, 1989; Harrison & Hulin, 1989; Morita, Lee, & Mowday, 1989; Murnane, Singer, Willett, Kemple, & Olson, 1991). Finally, a more disparate group of epidemiologists, sociologists, social workers, and social psychologists have been examining the prevalences and rates of more-or-less naturally occurring social phenomena such as family and relationship breakdowns (Felmlee, Sprecher, & Bassin, 1990; Fergusson, Horwood, & Shannon, 1984), rape prevalences (Russell & Howell, 1983), the duration of breastfeeding (Ryan & Dent, 1984), age at first intercourse (Kraft, 1991), and contraceptive discontinuation (Slonim-Nevo & Clark, 1989).

Despite the seemingly wide variety of survival analysis applications in the above list of studies, there are many large areas of psychology that would benefit by a greater use of these methods. In particular, community and ecological psychologists address many questions that could be answered with survival methods. Some examples include uncovering the factors influencing drug-use recidivism, the timing of juveniles' entrance into the justice system, prediction of violent behavior, modeling the birth and death of self-help groups, discovering the triggers to health-seeking behavior, understanding the influences of innovative program diffusion in the health care system, and discovering factors related to how long the effects last of a preventive intervention.

USING SURVIVAL ANALYSIS IN APPLIED PSYCHOLOGICAL RESEARCH

The mathematical and statistical underpinnings of survival analytic techniques can be difficult to understand. Fortunately, much of this technical background is unnecessary to be able to use, interpret, and understand survival analysis and its results. The following discussion is thus organized around three sets of practical issues a researcher typically needs to consider when performing a basic survival analytic study: (a) research design issues; (b) data preparation and organization; and (c) data analysis and interpretation.

Within each of these three general areas, many specific decisions have to be made. To provide a context for understanding how these decisions should be made, data from an existing study will be used whenever possible. The study is a large-scale evaluation of GROW, Inc. (Rappaport et al.,

1985; Roberts et al., 1991). GROW is a self-help organization for persons with a history of serious mental illness. The subset of the data presented here is used to model self-help group attendance (Luke, Roberts, & Rappaport, in press). Attendance and other data were collected over a 2 $\frac{1}{2}$ -year period from 861 members of 15 different GROW groups in central Illinois. Summary statistics indicated that about a third of the sample attended GROW for one or two meetings and then never returned. Another third attended GROW for several months and the last third attended for longer periods of time. Although these attendance pattern summaries are interesting, they do not shed much light on more in-depth questions such as when people are most likely to stop coming to GROW meetings, what types of people are the quick dropouts, and what the factors are that lead to long-term GROW involvement. The following sections show how survival analysis can help to answer these questions.

RESEARCH DESIGN ISSUES

Minimally, to perform a survival analysis one needs only to have two pieces of information for each case: the timing of a particular event, and whether the event is censored or not.⁵ However, behind this apparent simplicity lies a number of important and potentially troublesome design issues. (For other good discussions of research design and survival analysis, see Peto et al., 1976; and Singer & Willett, 1991.)

Event Timing

There are three issues that need to be considered about the timing of any particular event: event definition, event timing measurement, and the type of statistical model that will be applied to the event timing data. First is the definition of the event itself. Sometimes this is relatively straightforward, for example, the incarceration of a criminal or the pregnancy of an adolescent. (Note that these events may be difficult to measure; however, their definitions are relatively clear.) In other situations it may be more difficult to decide on a clear definition. For example, if marital breakup is the event of interest, what exactly constitutes that event? Should only formal divorces be counted, in which case the definition would be

⁵It should be noted that cases for survival analysis do not have to be persons, although they are in most of the examples discussed here. For example, the event of interest could be the dissolution of a self-help group, in which case groups are the cases, and group death is the event variable.

rather strict, or should the definition be broadened to include separations? Should other types of breakup such as death of a spouse be counted? Even when one decides on the categories to be included, there is the issue of when the event occurs. For example, assuming that only legal divorces are considered as marital breakup events, when does the divorce happen? The clearest time point may be the date of the final legal divorce decree. However, that may not be the most theoretically relevant time point. However difficult, the event must be defined so that it can occur only once for each person at a particular point in time. (The special cases of repeating events and multiple types of events are discussed later.) Essentially, the event being observed or measured should be treated like any important theoretical construct. It should be clearly conceptualized and defined so that it can be accurately and reliably measured.

In the case of the GROW attendance study, the event of interest is the point at which a person stops attending GROW meetings. Although this event is easy to define, it is much harder to operationalize and measure. The presence of an ongoing activity like group attendance is frequently easier to detect than its absence. Attendance is voluntary, and GROW members often show very different patterns of attendance. Some members attend every weekly meeting while others attend sporadically at best. (Indeed, it is this heterogeneity of patterns of attendance that makes it a substantially interesting phenomenon.)

The second issue concerning event timing has to do with whether it is measured continuously or discretely. For continuous time data, the timing of the event is measured precisely. For discrete time data, on the other hand, the event is known to occur within a particular time interval. For example, while the exact day that a person drops out of school might be known, the exact day a person became pregnant might not be as easily determined. However, pregnancy could be measured discretely, tying the pregnancy to a particular month. Conception may have occurred at any time during that month.

In reality, event data are neither discrete nor continuous; they lie somewhere on a continuum between the extremes. There are important substantive and statistical considerations to take into account when deciding on how finely or coarsely to measure event timing. First, the time interval should be selected so as to maximize the reliability and validity of the event duration variable. Again, consider a study of pregnancy. Although conception occurs at a specific time on a specific day, in reality there is no reliable way to exactly pinpoint the time of pregnancy (at least using the methods of social scientists). However, by collapsing the time data into weekly or monthly intervals, the measure of pregnancy timing becomes more reliable.

It may be argued that by using wider time intervals important information might be lost. The issue of lost information is actually a question of validity, and is determined by theoretical considerations. For example, if the primary goal of the pregnancy study is to show how demographic characteristics such as socioeconomic and ethnic background affect the timing of first pregnancies, then measuring the point of conception exactly will be of dubious benefit. Presumably, the effects of socioeconomic and ethnic status on the likelihood of pregnancy will be felt on a monthly or yearly time scale, not daily or weekly.

The GROW data set provides another example of how reliability and validity concerns shaped the decision of the appropriate time interval. Even though raw attendance data were collected on a weekly basis, it was decided to use monthly intervals for the survival analyses. Although most GROW groups met once a week, the research staff were not always able to attend every meeting in a month. By aggregating weekly attendance data into monthly intervals, it was less likely that we would misidentify someone as a dropout when they simply attended a meeting that we missed. Simple Monte Carlo experiments using the GROW attendance data indicated that monthly aggregation produced more reliable measures of overall attendance duration. This aggregation resulted in discrete event data measured on monthly intervals. If a person stopped attending GROW, we could identify what month that happened, but not the specific day or week. After aggregation, the event history data set consisted of 27 monthly intervals.

At this point in the design process, it is useful to consider what type of statistical model will be applied to the event data. There are two broad classes of survival models: continuous time and discrete time, and each is designed for its respective type of event time data (Allison, 1984). However, just as it is not always clear exactly how discrete or continuous a particular event time data set really is, it is also not always apparent what type of statistical model is most appropriate. Not surprisingly, continuous time survival models can always be applied to event data measured continuously; and discrete time models are similarly always appropriate for event data measured discretely.

However, it is often the case that continuous time survival models are used for discretely measured event time data. For example, MacKenzie (1991), using continuous time survival models in her study of parolees, summarized recidivism data using monthly time intervals. Similarly, Adler and Kandel (1983) used yearly intervals in their investigation of risk periods for substance abuse. In both cases the time intervals made theoretical sense, but how appropriate is it to use methods designed for continuous time data on discrete data? Statisticians generally agree that when the size of the time intervals are sufficiently small relative to the rate of event occurrence,

continuous time event models will produce results with little or no bias (Allison, 1982). However, as the size of the time interval increases, the size of the time-aggregation bias also increases (Heijtan, 1989; Petersen, 1991). In other words, it is safe to use continuous time models on discrete time data if the data are measured in small enough time units.

Until recently, however, there was no clear answer to the question of how small is small enough. Petersen (1991) has now provided some guidance for the optimal sizing of discrete time intervals. Using both statistical simulation and real data, he showed that when the underlying rate of event occurrence is less than .10 per time interval, the amount of time-aggregation bias is minimal, usually less than 5%. The time-aggregation bias is moderate (5 to 10%) for underlying event rates of .10 to .20 per time unit. So, for example, if it is known ahead of time that the rate of occurrence for a particular event is approximately .25 per month, then the investigator would be better off to use a weekly time interval, where the rate would be approximately .06 per week with an associated bias of less than 3%.

Despite greater calls for the use of discrete time survival models (Allison, 1982; Singer & Willett, 1991), they remain underutilized. The main reason for this is probably due to the relative difficulty of their use. Data sets must be transformed from single record per case to multiple record per case formats (Willett & Singer, 1991a). This usually requires fairly sophisticated programming to alter the record formats and create the dummy variables. Also, most of the major software packages do not have specific procedures for discrete time survival models. Instead, the researcher must use general purpose logistic regression procedures⁵. Survival and hazard plots must be reconstructed from the produced parameter estimates. Conversely, it is much easier to use the statistical procedures for continuous time survival models. Data sets require only minimal manipulation and the major software packages all have special-purpose integrated procedures that are (for the nonstatistician) much easier to use. Because of this, the rest of this primer will primarily focus on continuous time survival models.

Event Censoring

One often does not have complete information about the event history duration for particular persons. For example, a GROW member may not have dropped out of GROW by the end of the observational study, or a GROW member may have moved out of the state during the study. In either case we do not have a measure of the event of interest (dropping out of GROW). These are called *censored* cases. Figure 1 illustrates 7 different types of censored observations (based on a figure in Yamaguchi,

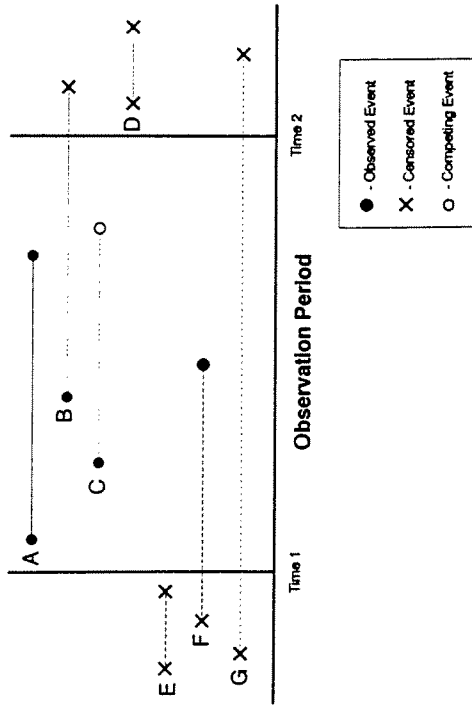


Fig. 1. Examples of censored and noncensored observation patterns.

1991). All participants are observed from Time 1 (T_1) to Time 2 (T_2), although events may occur both prior and subsequent to the observational period. The left endpoint of each participant's line marks the start of some event history, and the right endpoint marks the end of that history. The length of the line corresponds to the duration. Only Case A in Figure 1 shows an example of no censoring; the event duration begins and ends within the observation period of the study.

Event censoring may occur for one of two reasons. First, we may lack information due to the arbitrary limitations of the observational period. Events may occur either before or after the observational period, in which case event duration is not known to the researcher. In Figure 1, Cases B, D, E, F, and G exhibit this type of censoring. A second type of censoring occurs when a participant is lost to observation due to an event other than the event of interest.⁶ For example, in a study of school dropouts a participant might be lost because her family moved to a different city. This person should not be considered a dropout, however her exact event du-

⁶This is sometimes known as competing risks, because other events can occur that would exclude the event of interest from occurring. Competing risks can be modeled in their own right, and are discussed below.

ration is not known because of the move. Case C in Figure 1 is an example of this type of censoring.

Right censoring occurs when a participant has not exhibited the event of interest by the time observation ends, or the event duration has ended for reasons other than the event of interest. Cases B, C, D, and G in Figure 1 are examples of right-censored observations. One of the major advantages of survival analysis is its ability to handle right censored data. As long as censoring is unrelated to event occurrence, survival analysis can produce unbiased estimates of survival time summary statistics (Greenhouse, Stangl, & Bromberg, 1989). What this means is that the pattern of censoring cannot give us information about the likelihood of the event of interest. For example, in a study of job attendance, moving to a different state may be considered independent of the likelihood of staying home from work. On the other hand, death due to illness may be related to the event of interest—ill people are more likely to miss work for health reasons. Most of the major software packages allow the examination of censoring patterns in order to test for independence.

Although right censoring is well covered in the survival analysis literature, there is another type of censoring that is both more problematic and not often discussed. *Left censoring* occurs whenever duration information is missing because of events that happen before the start of the observational period. In Figure 1, Cases E, F, and G exhibit left censoring. One of the reasons that left censoring is not discussed as much in the literature may be due to the fact that left censoring never occurs in experimental designs where subject participation is controlled by the researcher. In this case, all participants enter into the study at the same time, and event durations cannot start before the observational period starts. However, *left censoring* may often occur in other types of designs, including quasi-experimental, retrospective, and archival studies. In general, survival analysis cannot adequately handle left-censored data. Therefore, it is imperative that left-censored cases not be included in a survival analysis.

For an example, consider the GROW attendance study. Many GROW members had been attending meetings before the research staff started observing the groups. Although the date these people stopped attending GROW could be observed, their starting date happened some time before the study began. This type of observation is represented by Case F in Figure 1. Even if we could know when they started (from self-report or GROW records), survival analysis would not be able to provide unbiased survival estimates. This is because by including all those persons who are already attending GROW at the start of the study, we are more likely to be including data from those persons who have attended GROW for rela-

tively longer periods of time. Persons who attend GROW for shorter periods of time are more likely to have started and stopped attending before the beginning of the observational period. An example of this is Case E in the figure. If left-censored cases are included, estimates of average survival times will be biased upward. Thus, for nonexperimental studies it is extremely important to make sure that no left-censored cases are included in the analyses. For the GROW data this is done by only including those GROW members who started attending GROW after the observational period started. (For a more detailed discussion of censoring and its implications see Little & Rubin, 1987; or Yamaguchi, 1991.)

DATA PREPARATION AND ORGANIZATION

Once a survival analysis study has been designed and the data collected, there are some data management steps that need to be done before the analyses can be performed. Many traditional multivariate methods can be performed on unmodified rectangular data sets. However, it is almost always necessary to translate from a raw data set into one that is appropriate for survival analysis. In particular the dependent variable, which is the event being modeled, is actually made up of two discrete pieces of information: the event time and the event status. The event time is a non-negative value that indicates the participant's time to event or response. Event time may be measured at any interval scaled level that makes sense for the particular study (e.g., seconds, days, months, years). Event status is a categorical variable that indicates if the event has occurred, or if it is censored. (Several computer programs allow multiple types of censoring codes to indicate, for example, if a subject is lost to follow-up, has not responded at end of study, etc.)

The first step in data organization is to calculate the event time variable. Sometimes this is relatively straightforward, as it would be in a study of school dropouts where the total number of months in school is directly recorded. In this case number of months in school is equivalent to number of months until dropout. If a person has not dropped out by the end of the study, the total number of months in school at the end of the study would be used in the event time variable. Other study designs may require more complicated data management. For example, in nonexperimental studies where participants can enter observation at varying times, the time event variable often must be calculated as the difference between a time-entered variable and a time-exited variable. In the GROW study time until dropout was calculated by subtracting the date the participant first attended

Table 1. Comparison of Raw and Translated Data Sets

| Case | Raw data set | | | Translated data set | | |
|------|--------------|----------|--------|---------------------|--------|--------|
| | Start date | End date | Gender | End months | Status | Gender |
| 1 | 05/06/84 | 07/28/84 | 1 | 3 | 1 | 1 |
| 2 | 05/07/84 | | 2 | 27 | 0 | 2 |
| 3 | 06/02/84 | 12/05/85 | 2 | 19 | 1 | 2 |
| 4 | 11/01/85 | 03/23/86 | 1 | 5 | 1 | 1 |
| 5 | 05/01/86 | | 2 | 3 | 0 | 2 |

a GROW meeting from the date of the last meeting attended. If a person was still attending at the end of the study, the last date of observation was used to calculate the time event variable.

To see this more clearly, consider Table 1. The left side of the table presents the raw data for five example cases from the GROW study. Each person has a start date, and those persons who stop attending during the observational period have an end date. If a person was still attending at the end of the study, they have no end date (indicated by a blank). (Remember, these cases are right-censored.) The right side of the table presents the translated data that can be used by the survival analysis. The event time variable "End Months" is simply calculated as the month after joining GROW that the person stopped attending. For example, Person 1 stopped attending in the third month after he or she started attending. Calculation of the event time variable is slightly more complicated for right-censored cases. Here, the end date is assumed to be equal to the date of the end of the study or observational period. For this example, the end of the study was July 31, 1989, 27 months after the start in May of 1987. Therefore, for Person 2 who attended the entire duration of the study, the event time variable is 27.

The event status variable indicates how the event time variable is to be interpreted by the survival analysis program. In this case, the status variable is coded 1 for a response, and 0 for a censored observation. A response means that the event of interest has occurred, in this case a person was observed who stopped attending GROW meetings. Thus in Table 1 Person 1 who was observed to drop out of GROW after 3 months has a status variable of 1, whereas person 5 who had been in GROW for 3 months at the time the study ended has the same event time value (3), but the event status variable would be coded 0 to indicate a censored observation.

Covariates are included in the data set just as they would be for a typical multivariate analysis. In Table 1, for example, each case has a value for the variable Gender, and this value is the same in both the raw and

translated data sets. Of course, any number of covariates may be included in the data set.

DATA ANALYSIS AND INTERPRETATION

Describing the Overall Survival and Hazard Functions

After the event of interest has been defined, the event durations have been observed, and the data have been translated, the first analytic step is often to examine the estimates of the overall survival and hazard functions. With this information you can discover some basic facts about the general pattern of survival times for the sample as a whole. In effect these estimates provide summary descriptive statistics for the event history data.

There are two commonly used nonparametric methods for estimating the overall survival functions. The *life table* or actuarial method groups the event durations into time intervals (e.g., weeks, months, years), summarizing the results in a life table. The *product-limit* or Kaplan-Meier estimate, on the other hand, uses ordered observations rather than grouped data (Kaplan & Meier, 1958). Here, all cases are ordered from shortest to longest event duration. The product-limit estimate has the advantage of producing results that are not dependent on the size of any time intervals, and is especially useful for small sample sizes (Slonim-Nevo & Clark, 1989). The product-limit and life table approaches yield identical estimates when there is no censoring and no ties (each time interval contains at most one observation) (Dixon, 1990). If you have discrete event time data and/or a large number of event duration ties, you should not use the product-limit estimate. However, if you have continuous event time data you can use either method.

Table II presents the life table for the GROW attendance data. (Unless otherwise noted, all statistical analyses were done using BMDP 1990 Version, programs 1L and 2L. All graphs were produced based on these data using Harvard Graphics for Windows.) A life table is a way of summarizing event history data. It is usually too detailed to appear in published journal articles, but it is important to understand how it is organized because the concepts of survival and hazard functions are based on information presented in the table.

Each row in the table represents one time interval, in this case a month. The entries in the *N* column indicate the number of cases that have survived (are still attending GROW) to the beginning of the current interval. So, for example, in the first month after joining GROW (the second line in the table) all 644 persons are still attending, since by definition you

Table II. Life Table for Overall GROW Attendance

| Interval start months | N | No. with-drawing (censored) | No. exposed to risk | No. terminal events | Pro-portion terminating | Pro-portion surviving | Cumulative proportion surviving | Hazard |
|-----------------------|-----|-----------------------------|---------------------|---------------------|-------------------------|-----------------------|---------------------------------|--------|
| 0 | 644 | 0 | 644.0 | 0 | .00 | 1.00 | 1.00 | 0.00 |
| 1 | 644 | 7 | 640.5 | 249 | .39 | .61 | 1.00 | .48 |
| 2 | 388 | 13 | 381.5 | 81 | .21 | .79 | .61 | .24 |
| 3 | 294 | 5 | 291.5 | 35 | .12 | .88 | .48 | .13 |
| 4 | 254 | 8 | 250.0 | 23 | .09 | .91 | .42 | .10 |
| 5 | 223 | 5 | 220.5 | 24 | .11 | .89 | .37 | .12 |
| 6 | 194 | 6 | 191.0 | 14 | .07 | .93 | .34 | .08 |
| 7 | 174 | 3 | 172.5 | 14 | .08 | .92 | .32 | .08 |
| 8 | 157 | 5 | 154.5 | 8 | .05 | .95 | .29 | .05 |
| 9 | 144 | 0 | 144.0 | 12 | .08 | .92 | .28 | .09 |
| 10 | 132 | 5 | 129.5 | 7 | .05 | .95 | .25 | .06 |
| 11 | 120 | 2 | 119.0 | 10 | .08 | .92 | .24 | .09 |
| 12 | 108 | 2 | 107.0 | 10 | .09 | .91 | .22 | .10 |
| 13 | 96 | 5 | 93.5 | 10 | .11 | .89 | .20 | .11 |
| 14 | 81 | 2 | 80.0 | 8 | .10 | .90 | .18 | .10 |
| 15 | 71 | 3 | 69.5 | 1 | .01 | .99 | .16 | .01 |
| 16 | 67 | 3 | 65.5 | 12 | .18 | .82 | .16 | .20 |
| 17 | 52 | 0 | 52.0 | 5 | .10 | .90 | .13 | .10 |
| 18 | 47 | 1 | 46.5 | 1 | .02 | .98 | .12 | .02 |
| 19 | 45 | 3 | 43.5 | 2 | .05 | .95 | .11 | .05 |
| 20 | 40 | 6 | 37.0 | 7 | .19 | .81 | .11 | .21 |
| 21 | 27 | 0 | 27.0 | 4 | .15 | .85 | .09 | .16 |
| 22 | 23 | 2 | 22.0 | 3 | .14 | .86 | .07 | .15 |
| 23 | 18 | 5 | 15.5 | 2 | .13 | .87 | .06 | .14 |
| 24 | 11 | 1 | 10.5 | 3 | .28 | .71 | .06 | .33 |
| 25 | 7 | 2 | 6.0 | 1 | .17 | .83* | .04 | .18 |
| 26 | 4 | 2 | 3.0 | 0 | .00 | 1.00 | .03 | .00 |
| 27 | 2 | 2 | 1.0 | 0 | .00 | 1.00 | .03 | .00 |

cannot drop out before you have started attending.⁷ The Number Withdrawing entries are the number of cases that are censored in that particular interval. For the first month after joining GROW, we see that seven persons are censored during this interval. These seven joined GROW very near the end of the study. They are still attending GROW at the end of the observation period and we do not know when, if ever, they stopped attending GROW. By the above definition they are right censored. The Number Exposed to Risk is defined as the number of cases entering the

⁷There is an important difference between the observation period of the study and the attendance period as presented in Table II. The 644 people who enter the analysis in the first month did not all start attending GROW in the first month of the study. Rather, they started sometime within the 27-month observation period. The first column in the table, Interval Start, always refers to the number of months a person has survived to, regardless of the month of the study.

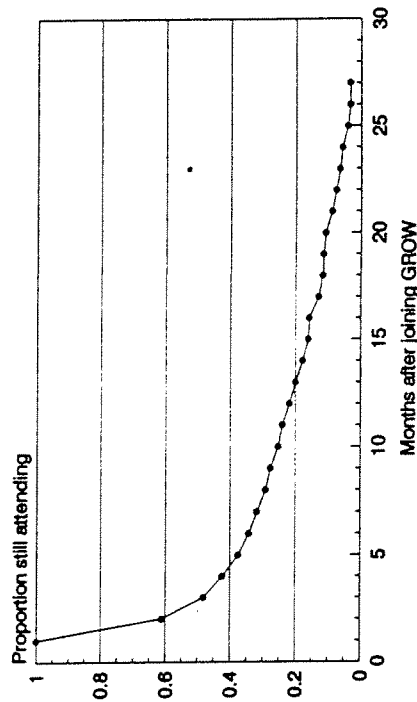
interval minus one half of those censored during the interval. By only including half of the censored group, the survival time statistics are adjusted to provide unbiased estimates. This number is calculated this way because censored observations have not been observed for the entire interval. The assumption is that they have been observed, on average, for half of the length of the interval. This assumption is one of the reasons that survival analysis can use censored data and produce unbiased survival estimates. The number exposed to risk is $644 - 0.5 * 7 = 640.5$. The Number of Terminal Events entry is the number of cases for whom the terminal event (stopping attending) has occurred in that interval. In the first month 249 people stop attending GROW. The Proportion Terminating is simply the number of terminal events divided by the number exposed to risk. The Proportion Surviving is one minus the proportion terminating. In the first month then, the proportion terminating is $249/640.5 = 0.39$, and the proportion surviving is $1 - .39 = .61$.

The last two columns in the life table actually provide the estimates of the survival and hazard functions. The Cumulative Proportion Surviving is an estimate of the probability of surviving to the beginning of the *i*th interval, or longer, without occurrence of the event. It is computed as the product of the proportion surviving this interval and the proportion surviving all previous intervals. For the GROW data, then, there is a 100% chance of surviving to the beginning of the 1st month. There is a 61% chance of surviving to the 2nd month ($1.00 * 0.61$), and a 48% chance of surviving to the 3rd month ($.61 * .79$). [Note that the estimated probability is not the same as the raw proportion of participants surviving. For example, the raw proportion surviving to the 2nd month is .602 (388/644). Only when there is no censorship is the estimate equal to the simple proportion. Again, this is because the survival estimate takes censored cases into account.]

Figure 2 presents the graph of the estimated survival function from the life table. The horizontal axis represents time, and the vertical axis shows the proportion of cases still surviving. The survival curve is a monotonically nonincreasing function, meaning that it can only stay the same or get smaller over time. To interpret the survival curve, you look at a number of things. First, the slope represents the length of survival time: a shallow curve means longer survival times while a steep curve indicates shorter survival times. Sudden changes in the slope over time indicates shifts in the probability of survival. The survival graph in Figure 2 indicates that a large number of the sample stop attending GROW very quickly, as shown by the steep curve at the beginning of the graph. After the first few months the curve flattens out, suggesting that the rate of dropouts slows down. The median survival time can be found by drawing a horizontal line from

the .5 point on the Y axis until it intersects the curve. For the GROW data the median survival time is 2.86 months (this is also printed out by the computer program), indicating that half of the sample has stopped attending GROW meetings in less than 3 months. The median survival time is a more useful summary statistic than the average survival time due to the existence of right-censored cases. For censored cases, we do not know exactly when the event will occur, if ever. Therefore, average survival time cannot be accurately calculated.

The last column in Table II presents the estimated hazard rate, which for continuous time models refers to the instantaneous rate of event occurrence, given that the event has not occurred up to that point. This is also known as the event risk.⁸ So whereas the estimated survival rate tells us how many people have survived up to some time point, the estimated hazard rate tells us the event rate for any particular person within a specific time interval, assuming they have survived to that time interval. In this case the time interval is 1 month. We see, for example, that the risk of dropping



(N = 644)

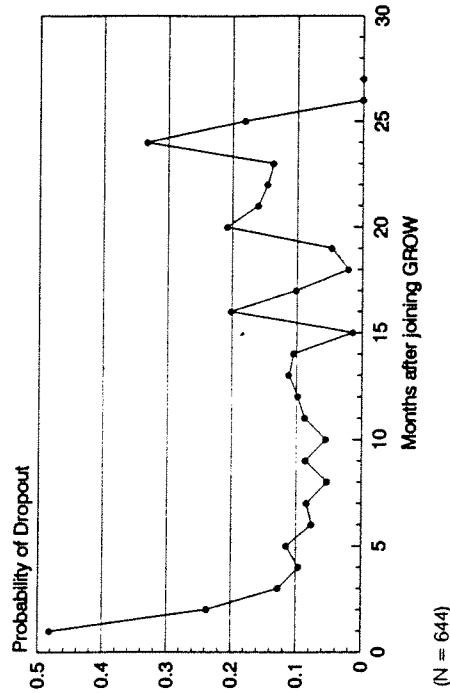
Fig. 2. Estimated overall survival function for GROW data.

⁸For discrete time models, the hazard rate is always calculated for each time interval, and can never exceed 100%. In this case the hazard rate is appropriately interpreted as the probability of occurrence in that particular time interval, given that the event has not occurred in a previous interval. However, when event times are measured continuously, there is no time interval. (More accurately, the time interval t is infinitely small.) In this situation the hazard rate can actually exceed 100%. The greater the risk, the more likely that the event will occur at that instant in time.

out of GROW is relatively high in the second month after joining (.24), provided that one has not dropped out during the first month. Again, the estimated hazard rate is not equivalent to the simple proportion of people terminating to number of persons exposed to risk within a specific time interval.⁹

Figure 3 presents the graph of the estimated hazard function for the GROW data. Each point on the graph represents the hazard rate for a particular month interval. It shows that the risk of dropping out of GROW is high for the first 2 months after joining, after which it levels off at approximately .08 to .10 for the next year. Around 15 to 18 months the drop-out risk starts rising again. This suggests that GROW members are most likely to drop out very early after joining. Also, if they stay in for at least 1.5 years, they become more likely to drop out after that time.

Examining the overall hazard function graph is a quick way to see how the rate of event occurrence changes over time. Used this way, the



(N = 644)

Fig. 3. Estimated overall hazard function for GROW data.

⁹Unlike with the estimated survival function, it is more difficult to see how the numbers for the estimated hazard rate are calculated. The equation for the estimated hazard rate is:

$$h_i = 2q_i/w_i(1 + p_i),$$

where q_i is the proportion terminating for some timepoint i , p_i is the proportion surviving, and w_i is the width of the time interval (SPSS Inc., 1991). This equation may not be intuitively obvious, but it has been found to be an unbiased estimate of the underlying population hazard rate (Gehan, 1975). So, for the first month after joining GROW, the hazard rate is $(2 * .39) / (1 * (1 + .61)) = .48$.

hazard function is much more substantively useful than the survival function because the latter can only decrease over time, while the former can go up or down depending on the underlying event probabilities. In fact, analyzing the shape of the hazard function is a primary task in survival analysis, as we shall see later.

Modeling the Effects of Covariates

A description of the overall survival and hazard functions can provide interesting information about the overall patterns of events over time. At the same time, however, these general curves based on the entire sample can mask theoretically important heterogeneity. When examining the effects of covariates on event durations, investigators can either examine single predictors one by one, or examine sets of multiple predictors.

Single Covariate (Subgroup) Analyses

Persons belonging to different subgroups defined by a single categorical covariate may exhibit quite different survival patterns. For example, girls in general may be less likely to drop out of school than boys. If this were the case, then girls would have a higher survival curve relative to the boys, indicating a higher proportion of girls staying in school for any particular point in time. Another typical situation calling for subgroup analyses is when survival times for an experimental group are compared to those of a control group. Subgroup analyses are probably the most common example of survival analysis found in the social science literature (e.g., Fisher & Anglin, 1987; Greenhouse et al., 1989; Isager et al., 1985; Ryan & Dent, 1984).

Subgroup analyses within survival analysis are quite straightforward. Essentially, a product-limit or life table is produced for each subgroup separately. Survival and hazard curves can then be plotted for each subgroup simultaneously, aiding in the interpretation of any subgroup differences. This can be done automatically by most of the statistics packages simply by specifying which categorical variable should be used. For example, specifying gender as a subgroup covariate would produce two sets of survival estimates: one for women and one for men.

Figure 4 shows the survival curves for an example subgroup analysis of the GROW attendance data. This analysis is based on a single categorical predictor: marital status. The graph indicates that persons who have never been married are more likely to stay involved in GROW, while those who are or were at some time married drop out of GROW at a relatively faster rate. Almost 40% of the persons who are or have been married drop

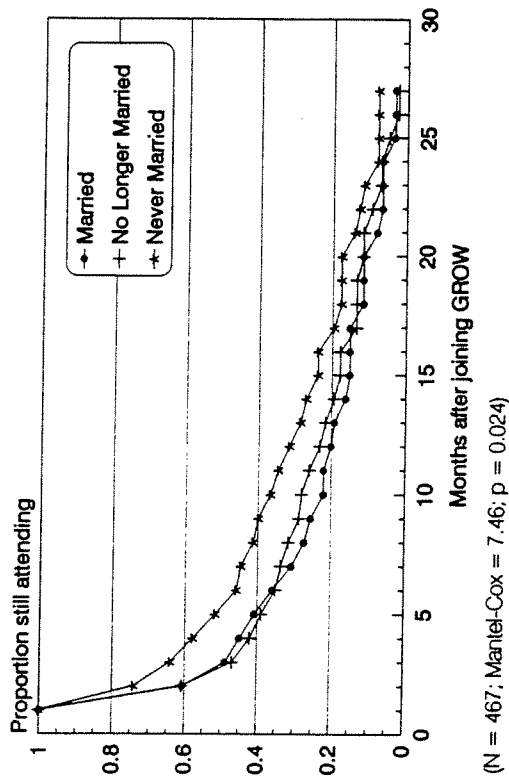


Fig. 4. Subgroup analysis: Duration of attendance by marital status.

out of GROW after only 1 month, compared to only 25% of the never married group. Also, the median duration of attendance for the married or previously married groups is slightly less than 3 months compared to just over 5 months for the never married group.

There are three common nonparametric statistics used to test the null hypothesis that there are no differences between subgroup survival functions based on single categorical predictors. Use of these statistics allows a more formal test of group differences than mere visual inspection would allow. Each of these statistics are log-rank tests that are variations of Wilcoxon tests (Hays, 1963). The most commonly used statistic is the Mantel-Cox, or simple log-rank test (Mantel, 1966), which applies equal weights to every time period. The Breslow statistic gives more weight to earlier observations, thus it is less sensitive to later events than the Mantel-Cox test. The Tarone-Ware statistic uses an intermediate weighting scheme and is a compromise between the Mantel-Cox and Breslow statistics (Dixon, 1990; Tarone & Ware, 1977). Unless there is a strong theoretical reason to employ a weighting scheme, the Mantel-Cox test should be examined first. For example, if you believe that the important effects of an intervention program will occur in the first few months after program participation, you might want to use the Breslow statistics to emphasize any early subgroup differences. This might be especially useful if you have a small sam-

ple, which would normally decrease your chances for discovering important subgroup differences.

A detailed discussion of sample size and statistical power relating to survival analysis is beyond the scope of this paper. The minimum required sample size depends on the desired effect size, the number of groups being compared, and the length of the observation period. Large numbers of censored cases reduce the power of the tests. Also, the tail of the survival curve often contains very few cases. This can sometimes make it more difficult to detect group differences. If you expect to see most of the interesting subgroup differences relatively early, then you can "cut off" the survival curve at the point where n becomes too small. Another possibility is to compare the Breslow statistic to the Mantel-Cox. If there is a significant group difference using the Breslow, but not the Mantel-Cox, then there is evidence that the largest group differences are occurring earlier on in time. Singer and Willett (1991) provide an excellent overview of this literature.

Multiple Covariate Analyses

Subgroup analyses, despite their usefulness, have two major limitations. First, by definition they are restricted to consideration of categorical variables. Continuous variables such as age can only be utilized after they have been transformed into categorical variables using rational or empirical criteria like median splits. This transformation results, of course, in a substantial loss of potentially important information. The second, and more serious problem is that only one covariate (categorical variable) can be analyzed at a time. Just as moving from simple regression to multiple regression allows more sophisticated modeling, the ability to handle multiple covariates greatly enhances the usefulness of survival methods.

In 1972, Cox presented a method that addressed both of these problems. The revolutionary article "Regression Analysis and Life Tables" described what is now known as the proportional hazards model. Not only does this method allow for multiple continuous and categorical explanatory variables, but these covariates can also be time-varying. Thus in a study of job transitions, socioeconomic status (categorical), age at time of first employment (continuous time-invariant), and salary at each yearly review (continuous time-varying) are all explanatory variables that can be simultaneously modeled using Cox's proportional hazards technique.

A major strength of the proportional hazards model is that it makes no assumptions about the form of the hazard function over time; it can take any shape whatsoever. By ignoring the exact shape of the underlying hazard

function, the focus shifts to how explanatory variables may or may not be related to the hazard function. Because the proportional hazards technique does not model the shape of the hazard profile, but it does model the effects of covariates on the hazard function, this is known as a semiparametric model. If an explanatory variable is related to the hazard function, then changes in this variable are associated with changes in the overall level of the hazard function in a linear fashion. That is, if an explanatory variable is related to hazard, this relationship will show up in a shift up or down of the hazard curve. For example, if men are likely to get arrested sooner than women after being released from prison, then a proportional hazards test of this hypothesis would show a hazard curve for men that has been shifted upward relative to that for women. The major assumption of the proportional hazards model is that for any two cases the ratio of their hazards is a constant across all time points (i.e., proportional) (Cox, 1972).

Table III shows the results of a proportional hazards model testing the relationship between a set of individual level variables and the probability of dropping out of GROW. Although somewhat cryptic, the material presented in this table provides a wealth of important information about the relationship between the covariates and the hazard function.

The first column of the table lists each of the covariates. In the next two columns the parameter estimate (coefficient) and its associated standard error are listed for each variable. The sign of each coefficient indicates the direction of the effect (if any) of the covariate on the hazard function. A positive coefficient increases the hazard function (shifting it up), thus decreasing survival time. So, persons with higher psychological functioning have a higher hazard rate, resulting in dropping out of GROW more quickly.

To determine which covariates are significantly related to the hazard rate, the ratios of the estimates to their standard errors can be examined. These ratios, listed in the fourth column, are z scores and are interpreted like t -tests in ordinary multiple regression. Thus, any ratio with an absolute

Table III. Proportional Hazards Model of Individual Level Variables^a

| Variable | Coefficient | Standard error | Coefficient/SE | Exp(coeff.) |
|---------------------------|-------------|----------------|----------------------|-------------|
| Gender | 0.1408 | 0.1473 | 0.9557 | 1.1512 |
| Age | -0.0126 | 0.0059 | -2.1133 ^b | 0.9875 |
| Marital status | -0.1978 | 0.0931 | -2.1242 ^b | 0.8206 |
| Educational level | -0.1265 | 0.0700 | -1.8067 | 0.8812 |
| Psychological functioning | 0.2077 | 0.0675 | 3.076 ^c | 1.2309 |

^aGlobal $\chi^2(5) = 20.34, p = .0011$.

^b $p < .05$.

^c $p < .01$.

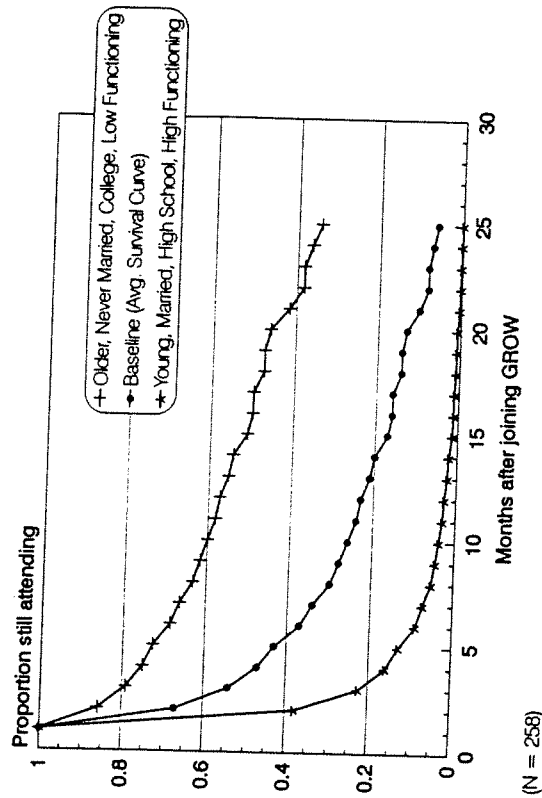
value over 1.97 indicates a significant covariate at the .05 alpha level. Table III shows that age, marital status, and psychological functioning are significant, with educational level showing a trend level effect.

The last column provides the most useful information for interpreting the effects of the covariates. The raw coefficient is difficult to interpret directly, because the Cox model is actually estimating the natural logarithm of the hazard rate. Interpretation becomes simpler if we exponentiate (take the antilog of the coefficient. [If d is the coefficient, compute $\exp(d)$; i.e., raise e to the d^{th} power.] Now for each unit increase in the explanatory variable, the hazard rate is multiplied by the exponentiated coefficient. For example, a unit increase in age results in the hazard rate being multiplied by 0.9875. Thus, the hazard rate is reduced by 1.25% for every year added to age. ($1.0 - .9875 = .0125$.) This type of interpretation holds for non-continuous variables as well: Moving from one lower level of psychological functioning to the next higher level results in a 23% increase in the hazard rate ($(1/1.2309)$). Taken together, these results show that GROW members who are young, married, and high functioning are more likely to drop out of GROW early than those who are older, have never been married, and are low functioning.

The proportional hazards model is an extremely flexible survival analysis technique, and it provides numerous ways to examine the data. Most Cox model algorithms allow for stepwise as well as manually specified covariate entrance and removal. (Although stepwise regression is possible, one should use this technique with extreme caution, especially for hypothesis testing. See Hocking, 1983; Lovell, 1983; Wilkinson, 1979.)

Another useful technique is to compare survival curves based on user-specified covariate patterns. These are also sometimes called covariate vectors. For example, consider a study examining the effects of gender and political orientation on political involvement. Gender is coded as 0 = female and 1 = male, and Politics is coded as 0 = liberal and 1 = conservative. Separate survival curves could be estimated for liberal males (1,0), conservative females (0,1) and so on. Most of the major computer packages allow any arbitrary covariate pattern to be used to estimate the survival function (see Appendix).

Figure 5 compares two extreme covariate pattern survival curves for the GROW data with the complete sample (baseline) survival curve. The first covariate pattern represents the best-case GROW member: older, never married, college degree or better and low functioning. These are the people who are most likely to stay in GROW the longest. The other curve is the estimated survival function for the worst-case members: younger, married, high functioning, and less than high school educated. The differ-



(N = 258)

Fig. 5. Comparison of baseline and covariate vector survival curves: Duration of attendance.

ences in the survival curves are striking. Within the first half year after joining GROW, essentially everyone who is in the latter group has dropped out, while the former group is likely to have over 35% still involved with GROW 2 years after joining. After identifying significant predictor variables via the Cox proportional hazards model, various covariate vectors can be constructed to help find out what types of people have what sort of survival patterns. This ability to jump back and forth between exploratory and hypothesis-testing modes of enquiry makes survival techniques intriguing and engaging tools.

Modeling Hazard Function Form

Although the above techniques are very powerful, they tend to impose a reductionist viewpoint on the analyses. That is, the survival analysis is interesting to the extent that individual variables or subgroups are found that are related to the overall survival curve or hazard function. The researcher never knows if important variables have been overlooked, or important subgroups missed. Use of the Cox semiparametric model is similar to an ANOVA or multiple regression approach—the focus is on the covariates rather than on the structural form of the overall hazard function.

However, another advantage of survival analysis is that it is not limited to an inspection of covariates. The overall form (i.e., shape) of the hazard curve over time can be examined and modeled. This can reveal important aspects of the event under consideration. For example, are children more or less likely to be absent as the school year progresses? Do computers break down randomly, or is it more likely within the first 72 hours, as some manufacturers suggest? Does the probability of drug use recidivism increase over time? These are all questions that can partially be answered by modeling the form of the hazard curves for particular events. The focus is on the probability of an event within a particular time period, not which variables may be related to that probability.

To model the form of the hazard function over time, a particular parametric model can be chosen. Choice of the appropriate model should be based on theory, although empirical results and statistical convenience usually come into play. Unlike the Cox semiparametric model, which intentionally ignores the form of the underlying hazard function, all fully parametric models estimate parameters for the hazard function. In general, a parametric model estimates two parameters describing the function. A location parameter indicates the average height of the hazard function, while a shape parameter shows shape or slope of the function. All hazard curves (and therefore, the functions that model those curves) can be categorized into one of three classes:

1. The hazard is constant over time. This means that the probability of the event occurring does not change as time passes. For example, in physics the probability of radioactive decay is constant over time. A graph of this curve would show a single horizontal line. The exponential model¹⁰ describes a flat, nonincreasing or nondecreasing hazard rate. Although the exponential model is easier to understand than other parametric models, its use is limited for social scientists. Most events of interest to social scientists have hazard rates that are dependent on time. Other parametric models must be considered when a nonconstant hazard rate is assumed.

2. The hazard either increases or decreases over time. As time passes, the probability of event occurrence gets either larger or smaller. This type of hazard is quite common. For example, in organizational psychology a theory of work attendance that views absences as a product of accumulated stress would hypothesize an increasing hazard rate over time. As stress builds up, a person is more likely to stay home from work. On the other hand, others have theorized that attendance is a habit. The more one stays

¹⁰Calling this the exponential model can be confusing, given that the model describes a flat, linear probability curve. Although the hazard is constant, the distribution of time until event occurrence is exponential.

at work, the more that the person is likely to continue staying at work. This results in a decreasing hazard over time (Harrison & Hulin, 1989). The two most common parametric models used to describe increasing or decreasing hazard rates are the Gompertz and Weibull models. Although they do differ from each other, these differences are often of more statistical than theoretical importance. (See Blossfeld et al., 1989, or Steinberg & Colla, 1988, for more detailed discussions of these parametric models.) The important similarity is that they both include parameters for the shape of the hazard function. The shape of the parameter is generally greater than one for an increasing function, and less than one for a decreasing function.

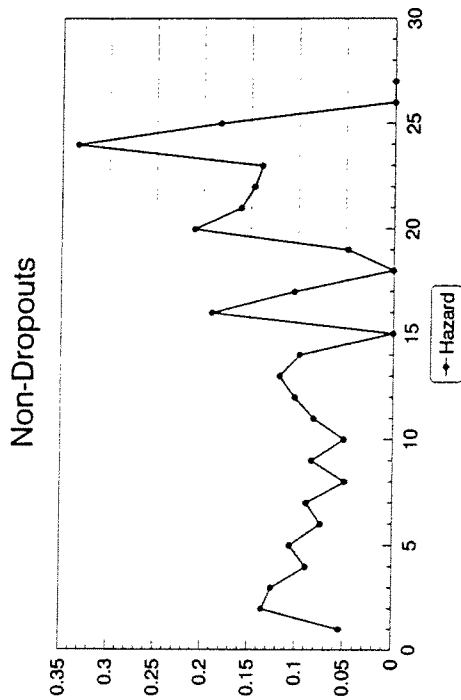
3. The hazard increases and decreases over time. In this case the hazard rate increases over some particular time span, and decreases over another. The most common example of this form is probability of death. The probability of death is fairly high early on in life, decreases as a person goes through adolescence and adulthood, and then increases in the later years of life. Unfortunately, there is no commonly used parametric model that describes U-shaped hazard curves such as this. On the other hand, two parametric models are available if an inverted U-shaped curve is proposed (low hazard, high hazard, then low hazard again): the log-normal and log-logistic.

As suggested above, the technical sophistication of these models often outpaces social theory. That is, our hypotheses and data usually are not precise enough to distinguish between the Gompertz and Weibull models, or the log-normal and log-logistic models (Allison, 1984).

How then, should these models be used in everyday applied research? Often, the most important task is to determine if the hazard rate is dependent on time in any simple fashion. This can be established by a few simple steps that are relatively straightforward and included in any survival analysis package that supports parametric modeling.

The first step should be to plot the hazard rate and examine it visually. Consider Figure 6, for example, which shows the hazard rate curve for a group of GROW members who attended at least 3 GROW meetings.¹¹ The plot indicates that for the first 1½ years after joining GROW, the risk of dropping out remains constant at about .08 to .10. After 18 months, the

¹¹A subgroup of the complete GROW attendance data set is being used here for two reasons. First, examination of the hazard rate for the entire sample suggests a U-shaped function (cf. Figure 3). As discussed above, it is not possible to adequately model this type of hazard curve. Second, other results suggest that the GROW sample is made up of two distinguishable populations: a group of persons who attend GROW once or twice and never come back, and those who attend semiregularly for months or years (Luke & Roberts, 1992). To validly model hazard rates it is important not to have more than one homogeneous population included in the analysis. See the discussion of unobserved heterogeneity.



(N = 342)

Fig. 6. Estimated hazard rate for non-dropouts.

hazard suddenly rises to somewhere between .15 and .20. Thus, this graph suggests that there is a long-term positive relationship between the hazard of dropping out of GROW, and the length of time of GROW membership. The next step is to test more formally the hypothesis that the GROW attendance hazard rate does increase over time. There are a variety of ways to do this. Lawless (1982) shows how to use residual plots to test for departures from exponentiality. (Remember that a constant hazard rate is described by an exponential function.) Another, more straightforward approach is to fit both the exponential model and one of the increasing/decreasing models such as the Weibull, and then test the relative fit of the two models (Allison, 1984). This works because the exponential model is a special case of the Weibull, Gompertz, and other models. The log-likelihoods of each model can be compared. (The log-likelihood is a goodness of fit statistic that derives from the maximum-likelihood estimation procedure in parametric models.) If the exponential model provides a poor fit to the data (i.e., the hazard rate is not constant over time), then its log-likelihood will differ significantly from that of the alternative model. This is similar to testing for a significant difference in change of R^2 in multiple regression. (See Kennedy, 1983, for a good introduction using log-likelihoods in this manner, and see Allison, 1984, for an application of this method to survival analysis.)

Table IV shows the results of fitting both the exponential and Weibull models to the GROW data. (This table is based on results obtained from

Table IV. Exponential and Weibull Parametric Models of GROW Data

| Covariate | Exponential model | | Weibull Model | |
|----------------|-------------------|------|---------------|-------|
| | Coefficient | SE | Coefficient | SE |
| Gender | -0.13 | 0.18 | 0.13 | 0.13 |
| Marital status | 0.17 | 0.11 | 0.08 | 0.08 |
| Education | 0.14 | 0.11 | 0.14 | 0.14 |
| Age | 0.44 | 0.08 | 0.13 | 0.13 |
| Location | 3.78 | 2.04 | 0.39 | 0.39 |
| Shape | 1.00 | | 1.21 | 1.21 |
| | | | 4.41 | 4.41 |
| | | | 1.81 | 1.81 |
| | | | 0.09 | 0.09 |
| | | | 13.25 | 13.25 |
| | | | 2.43 | 2.43 |
| | | | 2.95 | 2.95 |
| | | | 1.14 | 1.14 |
| | | | 1.15 | 1.15 |
| | | | 0.89 | 0.89 |
| | | | 82.3 | 82.3 |
| | | | 3.35 | 3.35 |

Log-Likelihood: -656.23

Log-Likelihood: -651.29

the SURVIVAL module of Systat.) Important covariates should be included in both models, and the covariate parameters are interpreted just as they are using the Cox model. Parametric models also estimate coefficients for the form (i.e., location and shape) of the underlying hazard model. The location parameter is usually not of any substantive interest. The shape parameter for the exponential model is constrained to 1.00, indicating that the hazard rate is assumed to be constant over time. For the Weibull model, the estimated shape parameter for these data is 1.21, indicating a possible increase in the hazard rate over time. (A value of less than 1 would indicate a possible decreasing hazard rate.)

The Weibull model contains all the variables included in the exponential model; in addition it includes the shape parameter. Any difference in the overall log-likelihoods of the two models is due entirely to this additional parameter. To test this, take the positive difference of the two likelihoods, and multiply it by two. This test value is distributed as a chi-square variable with degrees of freedom equal to the difference of the degrees of freedom of the two models (Allison, 1984). For the GROW data the difference between the two likelihoods is $656.23 - 651.29 = 4.94$. Twice this is 9.88. This value is compared to the chi-square critical value of 3.84 ($df = 1, \alpha = 0.05$). This significant result indicates that the exponential model does not adequately fit the data. Thus, there is evidence to suggest that the hazard rate for dropping out of GROW increases over time.

Although this process sounds complicated, it is actually much easier to do than to describe. By comparing the two log-likelihoods (which are similar to χ^2 statistics), we are simply finding out if there is evidence to suggest that the hazard rate changes over time. Because we found that there was a significant difference between the two models, we knew that the hazard rate must change over time, since the only difference in the two models was the inclusion of a shape parameter in the Weibull model. Furthermore, because the value of this shape parameter was greater than 1 (1.21), we also know that the hazard function increases over time. Referring to Figure 6 we can see that this test has confirmed what we already suspected from visual inspection of the estimated hazard function.

There is one problem common in survival analysis data that may lead to erroneous interpretations of hazard rates. If a sample actually consists of distinguishable subpopulations, each of which has a different but constant hazard rate, the hazard curve may appear to decrease over time even though every person in the sample has a constant hazard. This is known as the problem of *population heterogeneity* or *unobserved heterogeneity* (Blossfeld et al., 1989). Figures 7 and 8 illustrate this problem using a fictitious example. We have three subgroups of 100 individuals. Each subgroup has a constant hazard rate, but the level of hazard is different for

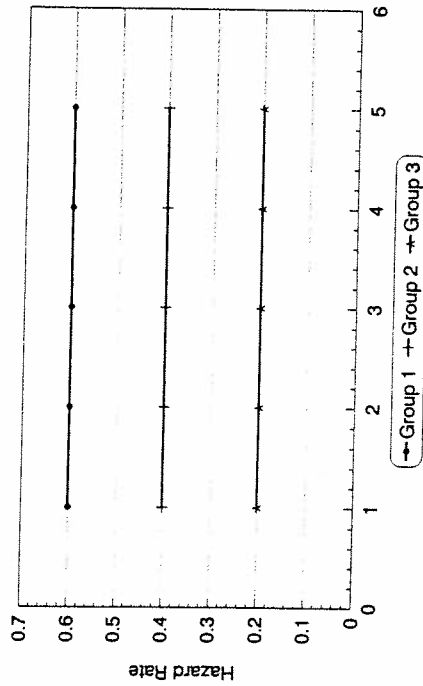


Fig. 7. Example of unobserved heterogeneity with three subgroups.

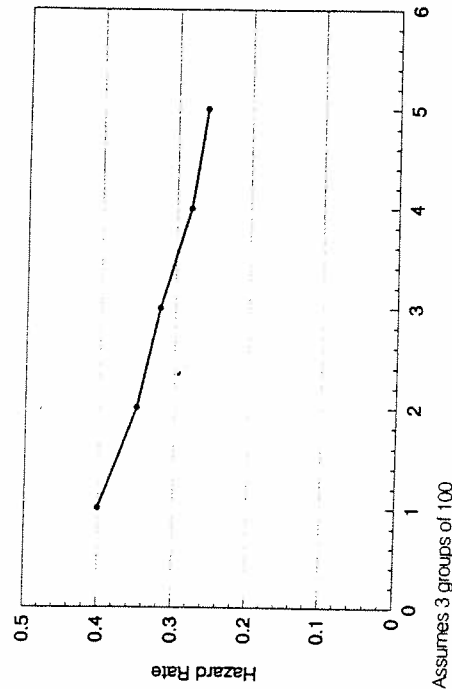


Fig. 8. Example of unobserved heterogeneity with three groups mixed together.

each of the groups. The hazard for Group 1 is 0.6, Group 2 is 0.4, and Group 3 is 0.2. If we analyze the subgroups separately, the correct hazard rates would appear as in Figure 7. However, if we analyzed the 300 persons together, the hazard rate would appear to decline over time, as shown by Figure 8. How does this happen? The individuals in Group 1, having a

higher hazard, are more likely to exit the sample earlier. (And conversely, the individuals in Group 3 are likely to stick around longer.) Thus, as time progresses, the average hazard for the entire sample decreases. This decrease, however, is a completely spurious effect due to the inclusion of different subgroups. The form of the underlying hazard function is constant, despite appearances! (You can work out this example for yourself by taking the numbers as presented in Figure 7. At each time point 60% of the first group will drop out, 40% of the second group, and 20% of the third group. Recalculate the average overall hazard rate after each time point.)

Fortunately, it is impossible to get spurious estimates of *increasing* hazard rates (Allison, 1984). That is, a problem of unobserved heterogeneity always acts to decrease the hazard rate. This means that whenever there is evidence to suggest that the hazard rate is increasing over time (as in our example), you can proceed to modeling without worrying about sources of unexplained heterogeneity.

ADVANCED METHODS AND ISSUES

The goal of this primer has been to provide an introduction to the basic techniques of survival analysis that are broadly applicable to a wide variety of data and are readily available in several major statistical packages. However, recent advances in statistics, biostatistics, sociology, and related fields have extended these basic techniques in several ways. Specifically, these newer methods can be applied to data that are richer or more precisely defined than the type of data often used in survival analysis. The following discussion briefly defines each of these methods, and points the reader to more detailed treatments.

Time-Varying Covariates

The Cox semiparametric model can be extended to include time-varying covariates. Time-varying covariates are those variables that can change value during the study or observation period. Thus, in addition to such typical time-constant explanatory variables as gender, other variables such as losing a job can be included in the model. The interpretation of results is straightforward: When a time-varying explanatory variable has an effect on the hazard rate, it will either cause the hazard to increase or decrease. For example, the loss of a job might increase the hazard of substance abuse recidivism.

Survival Analysis

Inclusion of time-varying covariates increases data collection and management difficulties. Time-varying information must be collected contemporaneously with the event data, although in some cases it is possible to gather this data retrospectively. Also, data files must be prepared differently if they include time-varying explanatory variables. The major software packages have increasingly started to include support for time-varying predictors. (See Appendix for a review of the major software packages.) Yamaguchi (1991) and Blossfeld et al. (1989) have excellent discussions of the Cox model and time-varying explanatory variables, including sample data and computer programs. Other good treatments include Allison (1984), Tuma and Hannan (1984), Kalbfleisch and Prentice (1980), and Cox and Oakes (1984).

Competing Risks

In the above discussion, it is assumed that the event under consideration is of one type. That is, 'dropping out of GROW' is one specifically defined event, and all instances of it are exactly alike. However, there are many times when the event being modeled may be thought of as a collection of similar events. For example, an analysis of job changes may include job transfers, retirement, being fired, and being laid off as different types of one general event. There may be times when a more detailed analysis of these different types of job changes would be appropriate. These different types of job changes are examples of competing risks. An employee is at risk at any time for any of these job change events. They are competitive in the sense that although any of them theoretically may occur at any time, only one can occur at any particular instant. A person can be fired or be transferred, but not both.

Fortunately, although competing risks introduces some theoretical complexity, its technical management is relatively simple. The solution is to model each specific event type separately. Thus, one analysis would be performed for job transfers, one for being fired, and so on. The overall hazard model for any type of job change is simply the sum of the type-specific models (Allison, 1984; Blossfeld et al., 1989; Carrol & Mayer, 1986).

Repeating Events

Just as survival analysis can be extended to handle multiple event types, it also can be generalized to deal with repeatable events. Although dropping out of GROW is not repeatable (at least the way it was defined), many events of interest to social scientists are. For example, pregnancy,

abortion, arrests, and psychiatric recidivism are all events that commonly happen more than once, even within relatively short time spans.

One approach to dealing with repeatable events is to include as an observation each period of time between events for any individual as a separate observation. Thus, the time from prison release to first arrest would be one observation, and the time from the first arrest to the second arrest (if any) would be another observation. The pooled observations yield a model that estimates effects for all of the arrest intervals at once. Allison (1984) provides a general discussion of the strengths and weaknesses of this approach, and Heckman and Borjas (1980) provide a detailed empirical example of modeling repeating events.

Sociology research has produced a set of models that are quite different from the hazard rate models discussed in this paper. These models include all of the above models as special cases, but instead of dealing with hazard rates, they focus on changes or transition rates between different states. A major advantage of these state change models is their ability to handle both repeating and multiple types of events simultaneously. Although no major statistics package can currently estimate these models directly, most parts of the models can be analyzed by typical survival analysis proportional hazards techniques. For more details see Coleman (1981), Tuma (1982), Tuma and Hannan (1984), and Tuma, Hannan, and Groeneveld (1979).

IMPLICATIONS FOR APPLIED PSYCHOLOGICAL RESEARCH

By now it should be clear that survival analysis is a powerful technique for understanding the timing and context of qualitative change. Survival analysis can handle different types of data (e.g., continuous, discrete, prospective, retrospective, and archival data) and can deal with censored observations without bias or loss of cases. Also, it can model events nonparametrically, semiparametrically, or fully parametrically. Finally, it can describe the survival and hazard rates for the entire sample or for subgroups, and it can characterize the effects of continuous or categorical covariates. In other words, using only a few pieces of easily collected data, a wealth of information about the form and process of an event can be discovered by survival analysis.

The examples described above illustrate the utility of these techniques. With just a few variables and fewer than six analyses we were able to discover quite a bit about the process of dropping out of GROW. The typical GROW member attended for 2.8 months, but almost 40% of GROW members drop out after only 1 month. For the entire sample, the probability of dropping out is greatest in the first 2 months and increases

again after 18 months of membership. More specifically, for those members who attend at least three meetings, the risk of dropping out is approximately .10 each month for the first 18 months of membership. After this the hazard increases to around .15 to .20. GROW members who have never been married, are older, or are lower functioning are the most likely to stay involved with GROW longer.

I conclude this primer with a short list of suggestions and/or tips that might be useful for anyone interested in using survival analysis. These have been gleaned from other survival analysis texts, studies using survival analytic techniques, and from my own experiences with teaching and using these methods.

1. Remember that under most circumstances survival analysis is able to handle event data measured at discrete time intervals. This means that survival analysis can often be used with the traditional longitudinal designs familiar to most social scientists. (I am specifically excluding the pre-post design. Although it is longitudinal, it is barely so!) Even if continuous time models are applied to event data measured discretely, the time aggregation bias can be minimized with appropriate choice of the size of the time interval. In other words, using survival analytic tools should not require substantial changes in study designs or methods. (Other longitudinal methods such as time-series analysis often require such changes.)

2. The use of archival or retrospective data, too often shunned in our field, can dramatically increase the utility of survival analysis. Event timing information is often recorded accurately in external data bases, and therefore represents a treasure trove to the intrepid researcher. For example, schools and organizations often maintain detailed absentee records. These can be used along with other information obtained from students or employees to model attendance, absenteeism, or dropouts. Also, depending on the type of event and the methods used to elicit the information, respondent retrospective reports can be highly reliable.

3. Most of the major software packages can competently handle the majority of the analyses described in this paper. However, there are some important differences between the programs. For example, not all of the major statistics packages currently handle time-varying covariates. (See Appendix for a more detailed discussion of these issues.) Although this can be somewhat frustrating, the output from various packages is usually clear and easily interpretable.

4. Much of the most interesting substantive results from survival analysis is graphical in nature (the survival and hazard functions, the subgroup curves, etc.) This makes it much easier to quickly grasp the important aspects of the event timing. Pictures of survival and hazard patterns really are worth a thousand words, and investigators should exploit the advantages

of visual displays of this information (Tufté, 1983). However, the graphs and plots produced by many of the survival analysis statistics packages leave much to be desired. Indeed, it may be necessary to replot the results before an accurate interpretation can be made. In particular, the plots of subgroup analyses often only become clear when they are redone using a more sophisticated graphics package such as Harvard Graphics or Freelance Graphics (to name just a couple).

5. You should exploit the power of survival analysis to examine the form of the underlying hazard function. Although covariate analysis is straightforward using the Cox regression model, by its very nature it limits the focus to how one set of variables is related to the event. Our field has traditionally emphasized such covariate-based analyses. By expanding our theoretical and empirical focus to include analyses of relationships among actors (via network analysis or cluster analysis) or relationships of events over time (time-series, growth curves, and survival analysis) we can better understand phenomena as whole entities rather than dissected slices of variance (Rapkin & Luke, 1993).

This primer has intentionally ignored a number of complex and important statistical issues. There are numerous statistical treatments of survival analysis available to deal with these issues, if needed. My purpose here, instead, has been to show how survival analysis can be used in a simplistic (but not simple-minded) manner to explore the richness of event data.

Survival analysis is a powerful tool. If we start including it in our analytic toolbox we will be better able to understand events and the qualitative changes that they represent. In turn, we will be able to develop social and psychological theories that have time and change as integral aspects.

APPENDIX: COMPUTER PROGRAM CONSIDERATIONS

Investigators interested in survival analytic techniques will be happy to find that there are several statistical computer packages that offer powerful survival analysis procedures. This has not always been the case. Just a few years ago, Goldstein et al. (1989) reported that although the available PC-based survival analysis packages gave accurate computational results, these programs had a long way to go. In particular, they noted the extremely poor documentation, lack of program flexibility, lack of diagnostic features, and general difficulty of use.

Since then the quality of survival analysis software has improved noticeably. In this Appendix, I briefly discuss four major software packages that have comprehensive procedures to analyze event duration data. The four packages have been chosen (BMDP, SAS, SPSS, and SYSTAT) be-

cause they are the most widely available and most frequently used by social scientists. I caution the reader that although the information presented here is, to the best of my knowledge, accurate at the time of writing (early 1993), it may become outdated rather quickly.

Table A1 summarizes the survival analysis features found in the four statistics packages. At the top of the table the specific version and platform are listed for each program. Features often vary between platforms for the

Table A1. Comparison of Survival Analysis Computer Packages

| | BMDP | SAS | SPSS | SYSTAT |
|--------------------------------------|-------------------------------------|---|---|----------------------------------|
| Package version and platform | BMDP 1990; Mainframe version 1L, 2L | SAS Version 6; Mainframe version LIFETEST, LIFEREG, PHREG | SPSS for Windows Release 5; IBM PC SURVIVAL, KM, COXREG | SYSTAT 5.02; IBM PC Survival 1.0 |
| Breadth of features | Good | Excellent | Fair | Fair |
| Ease of use | Fair | Poor | Excellent | Good |
| Graphics | Fair | Fair | Good | Good |
| Documentation | Fair | Fair | Fair | Fair |
| Nonparametric analyses | | | | |
| Survival estimates | Life Table; Product-Limit | Life Table; Product-Limit | Life Table; Product-Limit | Product-Limit |
| Aggregated data | Yes | No | Yes | Yes |
| Rank tests | 3 | 2 | 3 | 3 |
| Censoring & failure pattern analysis | Yes | Yes | No | Yes |
| Semiparametric analyses | | | | |
| Cox proportional hazards | Yes | Yes | Yes | Yes |
| Stepwise models | Yes | Yes | Yes | Yes |
| Covariate vector models | Yes | Yes | Yes | Yes |
| Time-varying covariates | Yes | Yes | Yes | No |
| Parametric analyses | | | | |
| Fully parametric models | Yes | Yes | No | Yes |
| Covariates | Yes | Yes | No | Yes |
| Stepwise models | Yes | No | No | Yes |

same program. For example, currently in SPSS many of the advanced survival analysis procedures (e.g., Cox proportional hazards modeling) are only available in the Windows version, not in the mainframe or regular DOS versions. For each package the specific survival analysis procedure names are listed. In the case of SYSTAT, the survival analysis routines are part of a separate module that does not come with the basic SYSTAT package; it must be purchased separately. SPSS for Windows is currently provided in three separate packages; all of the survival procedures are found in the Advanced Statistics module.

General Features

After the procedure names, I rate the programs on breadth of features, ease of use, graphics, and documentation. These are simple subjective ratings, and are meant only to highlight the relative strengths and weaknesses of the packages. SAS clearly stands out with regard to the variety of things that can be done with the survival procedures. For example, SAS is the only procedure that allows the user to specify how event duration time ties should be handled by the program. However, perhaps because of the depth of the program, SAS is also the most difficult to use. SAS puts a lot of power into the hands of the analyst, but it is clearly not meant for the novice user. SPSS for Windows stands in sharp contrast. Its modern graphical interface, support for interactive data management and analysis, and speedy operation make it by far the easiest survival analysis package to use. (At the time of this writing SAS and SYSTAT both had just released Windows versions of their software. However, the SYSTAT Windows package did not include the survival analysis procedures, and the SAS package was not available to the author.)

Not surprisingly, graphics support is weaker in the mainframe packages. SPSS with its Windows environment makes it extremely easy to get quick graphics output of survival and hazard plots. SYSTAT, with its integrated Sygraph graphing facility, provides more powerful support, although it is somewhat harder to use.

Documentation remains a frustrating aspect of these programs. Although there are some strengths, the documentation is generally poorly structured and hard to understand. Although all provide programming examples, there could still be more coverage of tricky procedures, such as how to include time-varying covariates in the model. The documentation for SAS' LIFETEST and LIFEREG procedures is particularly dense and unhelpful. The PHREG documentation comes in the form of a technical report, and is much more thorough with many helpful examples complete

with data and program output (SAS Institute, 1990). It is still written, however, with the statistical professional in mind. The SPSS documentation has the most attractive presentation and is the easiest to read, but is only minimally helpful with how to do complicated analyses. The SYSTAT survival package comes with its own extensive 154-page manual. It is very readable and is the only set of documentation reviewed here that tries to educate the reader about survival analysis as well as describing the program. It includes an index and an adequate reference list. Despite its thoroughness the documentation seems unorganized at times; also, the examples could be more extensive. The BMDP documentation, on the other hand, is organized clearly but the presentation is too often cryptic.

Nonparametric Analyses

All four of the statistics packages competently produce nonparametric estimates of survival and hazard functions, and can perform rank tests for subgroups based on single categorical predictor variables. There are no major limitations in any of the implementations of these procedures. There are a few minor differences between the programs. All the programs except SAS can estimate survival and hazard functions for aggregated data. (Instead of having event duration times and censor information for each case, aggregated data are in the form of counts per time interval.) In addition to the overall test score for comparing survival curves of subgroups defined by a categorical predictor variable, SPSS can automatically compare each pair of categorical factor levels. This must be done manually in the other programs. SYSTAT lacks the ability to produce survival estimates based on the life table approach. Finally, all of the packages except SPSS provide simple plots of censoring and survival pattern times. These plots are useful for detecting if censoring is truly independent from survival times.

Semiparametric Analyses

Support for Cox proportional hazards modeling is particularly strong for all of these programs. In fact, except for SYSTAT's inability to handle time-varying covariates, these procedures look remarkably similar. Both SAS and SPSS offer a wide array of diagnostic plots, used to test for violations of the proportional hazards model. SPSS can provide these plots automatically, while in SAS they must be specifically programmed.

While support for time-varying covariates is one of the major strengths of the proportional hazards model, neither BMDP, SPSS, nor SAS make it easy to perform these analyses. For example, if you would like to include

a time-varying predictor that is not a simple function of time, BMDP requires you to write a separate FORTRAN subroutine. SAS seems to have the best support for this type of analysis.

Parametric Analyses

All of the packages except for SPSS support a variety of parametric models in very similar ways. The documentation for SYSTAT provides a nice summary of how to interpret the various parametric coefficients such as shape and scale. None of the programs provide enough examples in their documentation for parametric models.

Summary

For the most part, any of the four statistical packages discussed here can be used to perform the types of survival analyses discussed in this primer. If you need straightforward estimates of survival and hazard functions, or simple tests of the effects of covariates on these estimates, any of these packages will suffice. Although the focus of this primer has been on continuous time survival models, it should be noted that the logit regression procedures in these statistics packages can also be used to perform discrete time hazard modeling.

There is still a lot of room for improvement. None of the packages at this time can automatically handle competing risks or repeating events. Support for time-varying covariates could be improved. It would be nice to see discrete time models integrated into the survival procedures, rather than having to turn to the general logit regression procedures. Finally, the documentation for all the packages could be improved.

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