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From Whether to When:
New Methods for Studying Student Dropout
and Teacher Attrition

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Educational researchers studying student dropout and teacher attrition typically ask whether specific events occur by particular points in time. In this article, we argue that a more powerful and informative way of framing such questions is to ask when the transitions occur. We believe that researchers avoid asking questions about time-to-event ("When?") because of methodological difficulties introduced when members of the sample do not experience the target events during the data collection period. These people—the students who do not graduate or drop out, the teachers who do not quit—possess censored event times. Until recently, statistical techniques available for analyzing censored data were in their infancy. In this article, we show how the methods of survival analysis (also known as event history analysis) lend themselves naturally to the study of the timing of educational events. Drawing examples from the literature on teacher attrition and student dropout and graduation, we introduce a panoply of survival methods useful for describing the timing of educational transitions and for building statistical models of the risk of event occurrence over time. We hope that this non-technical introduction to survival methods will help educational researchers articulate and explore important substantive questions that they have raised but have yet to answer.

Researchers studying student dropout and teacher attrition patterns typically ask whether critical transitions occur by particular points in time. In their seminal reviews of the literature on college attrition, for example, Spady (1970), Tinto (1975), and Terenzini and Pascarella (1980) present models of whether freshmen drop out after one semester or one year or whether students persist and graduate four years later. Similar questions arise when studying other events marking the educational lifespan, including: entry into and exit from day care (Singer, Fosburg, Goodson, & Smith, 1980; Whitebook, Howes, & Phillips, 1990), entry into and exit from special education (MacMillan, Balow, Widaman, Borthwick-Duffy, & Hendrick, 1990; Walker, Singer, Palfrey, Orza, Wenger, & Butler, 1988; Wolman, Bruininks, & Thurlow, 1989), dropout and graduation from high school (Bryk & Thum, 1989; Natriello, 1987; Rumberger, 1987), entry into and graduation from advanced degree programs (Buckley & Hooley, 1988; Girves & Wemmerus, 1988), and entry into and exit from the teaching profession (Chapman, 1984; Grissmer & Kirby, 1987; Heyns, 1988; Theobald, 1990).

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In this article, we show that much more could be learned about educational transitions if investigators answered their research questions about *whether* events occur by modeling *when* the events occur. Rather than asking whether students dropout before the end of the senior year, they should ask: When are they at the greatest risk of dropping out? Rather than asking whether teachers quit the profession after two years of service, they should ask: When are they at the greatest risk of quitting? Although logically intertwined, these two types of questions are also conceptually distinct, the "When?" question being far more general than the "Whether?". In fact, as we will show, by asking when events occur, a researcher learns not only whether these events occur by each of several points in time but much more.

Before proceeding, let us play devil's advocate: If the answer to the "When?" question is so much more illuminating, why do researchers typically ask the "Whether?" question? Although we cannot know for certain, we believe that one reason has been severe analytic and logistical constraints. Until recently, statistical methods appropriate for answering the "When?" question have been sorely lacking, and empirical researchers tend not to ask questions that they lack the wherewithal to answer.

To answer "When?" questions using familiar statistical techniques such as regression analysis or analysis of variance, the value of the outcome—time—must be known for every person under study. Few research designs meet this requirement. No matter when data collection begins and no matter how long any subsequent follow-up, some study participants do not experience the target event while the researcher watches—some students do not drop out; some children do not leave day care; some teachers do not quit. These people have *censored* event times. What value of the outcome should they be assigned? Will they experience the event soon after the end of data collection, or will some of them never undergo the transition of interest? For individuals who possess censored event times, all the researcher knows is that by the end of data collection the event had not yet occurred.

Censoring creates an analytic dilemma: What should be done with people who do not experience the target event during the period of data collection? Although the researcher knows something about them—if they ever experience the event, they do so after data collection ends—this knowledge is imprecise. We believe that this implicit uncertainty may explain the appeal of the alternative "Whether?" question. Asking whether the target event occurs by a particular time, especially if the selected cutoff time has substantive or policy-related significance, is clear-cut despite censoring. Researchers studying student persistence may not know the career durations of all their sampled students, for instance, but they can still reasonably ask whether members of a college freshman class graduate in 4 years. Divisions of the sample into two groups (those who graduated in 4 years vs. those who did not) sets the stage for using logistic regression analysis or discriminant analysis to model the categorical outcome—graduation—as a function of the students' background, training, financial status, and so forth (e.g., see Ott, 1988; Stage, 1988, 1989).

But dichotomization can obscure knowledge about educational transitions. Sample splitting eliminates potentially meaningful variation in event times by clustering together everyone who graduates before, and after, the chosen cutoff. Students who graduate in 3 years are not distinguished from those who graduate in 4. Students who graduate in 5, 6, 7, or 8 years are also pooled. Any particular dividing time, even one

relevant to the process under study, is somewhat arbitrary; many students do, after all, graduate after 4, 5, or 6 years of college. And dichotomy-based analyses of student careers—whether high school or college—are likely to become increasingly invalid in the 1990s and beyond as once nontraditional educational trajectories become the norm. Consider, for example, whether a 4-year graduation cutoff remains appropriate now that only 15% of college freshmen graduate within 4 years (Porter, 1990) and that one third to one half of high-school dropouts eventually receive a high-school diploma or a General Education Development (GED) certificate (Frase, 1989; GED Testing Service, 1986; Kirsch & Jungeblut, 1986; Kolstad & Owings, 1986). Dichotomizing and asking whether an event occurs by a particular point in time do not resolve the censoring dilemma; they simply obscure it from view.

Dissatisfied with the dichotomization approach, some researchers do ask when events occur, but censoring often hampers their efforts. Some try to resolve the censoring problem by imputing event times for censored people, usually setting unknown event times equal to the length of data collection. When studying the career persistence of special educators during a 5-year period, for example, Frank and Keith (1984) assigned career lengths of 5 years to teachers still teaching when data collection ended (see also Kahn & Kulick, 1975). These researchers should be complimented for their thoughtfulness—all the censored teachers did teach for at least 5 years. Many, however, taught for much longer than this. So imputation systematically underestimates overall career length because the ultimate event times for censored teachers are necessarily greater than the imputed value.

Other researchers try to resolve the censoring dilemma via research design by focusing exclusively on the noncensored individuals. When studying how long it took doctoral students at UCLA to graduate, for example, Abedi and Benkin (1987) analyzed data on only those students who had already completed their degrees. But omitting students whose studies are still in progress modifies the target population to only those who have already successfully completed, thereby altering the research question. The average time to degree among all students must be longer than that found among those who have already graduated.

Sound quantitative study of educational transitions requires statistical methods that deal evenhandedly with censoring. Although a comprehensive set of such techniques was unavailable until recently, the methods known as survival analysis, event history analysis, or hazards modeling have changed how researchers can study time. Originally developed by biostatisticians modeling human lifetimes (Cox, 1972; Cox & Oakes, 1984; Kalbfleisch & Prentice, 1980; Miller, 1981), these methods have been extended by economists and sociologists modeling social transitions (Allison, 1982; Blossfeld, Hamerle, & Mayer, 1989; Mayer & Tuma, 1990; Tuma & Hannan, 1984) and engineers modeling industrial product reliability (Lawless, 1982). Differences in labels and substantive fields aside, we believe that these techniques will prove valuable in education as well, for they provide a sound mathematical basis for simultaneously exploring when (and, consequently, whether) events occur (Willett & Singer, 1989). Specific techniques within the broad class of methods enable researchers to describe temporal patterns of occurrence, compare these patterns among groups, and build statistical models of the risks of occurrence over time.

In this article, we introduce the principles of survival analysis, showing how they apply naturally to research questions about educational transitions. Rather than offering a general technical discussion or a thorough substantive review, we present

the methods by examining the analytic approaches that researchers have used to study two types of educational transition: teacher entry into and exit from teaching and student entry into and exit from school. This organization highlights the important contribution of previous researchers who, although perhaps unaware of the formal principles of survival analysis, developed summary statistics, descriptive strategies, and graphical displays that fit squarely within the framework. Placing their approaches within the new framework allows us to take advantage of methodological advances from other disciplines and posit innovative and informative ways of modeling educational transitions. We are convinced that the sensitive microscope of survival methods has the potential to reveal much about educational processes, much that currently remains hidden.

Research on Teacher Career Paths

As United States public schools emerge from the enrollment declines of the 1970s and 1980s, rising birth rates and increasing teacher retirements have raised the specter of a teacher shortage (National Academy of Science, 1989; National Education Association, 1987). Whether a shortage will arise depends, in part, on the career decisions of hundreds of thousands of former, current, and future teachers. Educational administrators, planners, and researchers seek answers to questions such as: Will licensed teachers take teaching jobs? Will current teachers stay in the classroom? Will former teachers return? Below, we review the statistical methods that have been used to investigate such questions, and we show how many of them can be subsumed under the unified framework provided by survival analysis.

Two-Wave Studies

Most quantitative research on teacher career paths has been descriptive, focusing on determining how many of the nation's current teachers are likely to remain in the classroom. One of the simplest descriptions is the teacher *attrition rate*, an estimate of the proportion of teachers employed in a specific jurisdiction (a school district, a set of school districts, or a state) who leave their jobs during a finite period of time, usually 1 year. In their extensive review of the teacher career path literature, for example, Grissmer and Kirby (1987) present annual attrition rates in Illinois, Michigan, New York, and Utah culled from state reports covering the period 1979 to 1982. Thoughtfully discounting 1980 as an exception (because reductions in force wreaked havoc on the schools), Grissmer and Kirby reported that approximately 6% of the teachers employed in any given year were gone the next. Simple annual attrition rates remain the workhorse of teacher career path research, appearing routinely in school district and state reports on the topic (e.g., Carter, 1981; Cavin, 1986; Mayfield, 1982; Oliver, 1980; Parshall, 1990). The National Center for Education Statistics also uses a 6% annual attrition rate for its midlevel projections of teacher supply and demand (Gerald, Horn, & Hussar, 1990).

While federal, state, and local policymakers and researchers often see the glass as partially empty (and ask how many teachers leave the schools), academic researchers often see the glass as partially full (and ask how many teachers stay). Instead of estimating the teacher attrition rate, they estimate the teacher *retention* or *survival rate*—the proportion of teachers in 1 year who continue to teach the next. We can easily compute one rate from the other; we could reexpress Grissmer and Kirby's results, for example, and conclude that approximately 94% of teachers survive

(continue to teach) between 2 consecutive school years. Estimated teacher survival rates abound in the research literature (e.g., see Charters, 1970; Mark & Anderson, 1978, 1985; Schlechty & Vance, 1981; Theobald, 1990; Whitener, 1965) and, as we will show, under certain conditions, these rates extend naturally into the genre of survival analysis.

Recognizing the brevity of a 1-year interval in the context of an entire teaching career, some researchers extend their time perspective and estimate multiyear survival rates. Lacking a substantively meaningful cutoff point (such as senior year for high-school and college students), most researchers present 5-year rates. Although the 5-year time frame is somewhat arbitrary, these rates are appealing because they capture behavior over moderate stretches of time, because they were used by the pioneers in this research area (e.g., Charters, 1970; Whitener, 1965), and because they resemble the 5-year survival rates used by physicians to report the life expectancy of patients after surgery or disease diagnosis. In her analysis of data collected as part of *The National Longitudinal Study* (NLS), for example, Heyns (1988) found that 60%–70% of the NLS sample who became teachers were still teaching (surviving) after 5 years in the classroom. Even more striking is the robustness of the 60% 5-year survival rate across studies that used very different target populations, including: the nation (e.g., Heyns, 1988), newly hired teachers in a set of metropolitan St. Louis school districts (e.g., Chapman, 1984; Whitener, 1965), and graduates from several different large schools of education (e.g., Chapman & Hutcheson, 1982; Frank & Keith, 1984).

Attrition and survival rates computed across 1 or more years provide common-sense summaries of whether teachers leave teaching. They have been, and should remain, a valuable component of any researcher's methodological tool kit. But, when presenting these simple summaries, an important caveat is in order. Attrition and survival rates are comparable only if they are computed on comparable groups of teachers. Some researchers compute these rates for the entire teaching force in a jurisdiction (e.g., Lauritzen & Friedman, 1991; Parshall, 1990; Theobald, 1990) while others restrict attention to newly hired teachers (e.g., Mark & Anderson, 1978, 1985; Murnane, 1987). If the likelihood of leaving teaching differs across the teaching career (as it does), attrition or survival rates computed for the entire teaching force depend not only on teachers' propensity to leave but on the distribution of experience in the cohort under study. For this reason, we reaffirm the message of Grissmer and Kirby (1987), who urge researchers "to follow samples of teachers from their point of entry into the profession over time to investigate more fully the causes of attrition" (p. 74). Although much can be learned from data collected on the entire teaching force, the clearest signals about teachers' careers will come from studying cohorts of teachers whose professional lives were tracked from a common reference point—their entry into teaching.

Multiwave Studies

Many researchers argue convincingly that two-wave comparisons, even those separated chronologically by several years, offer limited insight into how, why, and when teachers leave their jobs (e.g., Haggstrom, Darling-Hammond, & Grissmer, 1988; Heyns, 1988; National Academy of Science, 1987). Longitudinal data permit a more refined and realistic view of a teacher's career, an ability to track factors associated with teachers' stay or leave decisions, and increased statistical power as well.

Responding to the need for comparable data across teachers, most multiwave studies track one or more cohorts of new teachers over time, noting each person's employment status along the way. Aggregation of individual career histories allows computation of the proportion of new teachers that continue to teach in each successive year for as many years as data collection continues. Although time-consuming and expensive to collect, multiwave data sets have been assembled by several teams of researchers, including: Charters (1970); Murnane, Singer, and Willett (1988, 1989); Murnane, Singer, Willett, Kemple, and Olsen (1991); Schlechty and Vance (1981); and Mark and Anderson (1978, 1985). Mark and Anderson, in an early and trend-setting investigation, followed more than 15,000 metropolitan St. Louis teachers for as long as 13 years, documenting the large proportions of newly hired teachers who left after only a few years in the classroom.

Data collected under the multiwave paradigm lend themselves naturally to survival methods. The survival analysis literature uses the term *survival probability* to refer to the proportion of an initial cohort of teachers surviving through each of several successive years and the term *survivor function* to refer to plots depicting the pattern of survival probabilities over time. Sample survivor functions provide simple and compelling summaries of the teaching career in aggregate.

In the top panel of Figure 1, we use data describing the career paths of 3,941 special educators hired in Michigan in the early 1970s to illustrate the application of the survivor function (Singer, 1992).¹ The panel presents sample survivor functions indicating the proportion of women and men who survived through their 1st year of teaching, their 2nd year, their 3rd year, and so on, up to the 12th year. Like most survivor functions describing teachers' careers, these curves slope downwards quite steeply in the beginning and then level off as time passes. When the teachers are newly hired (at the "beginning of time"), they are all surviving by definition, and the survival probabilities are 1.00. As the career progresses, teachers leave their jobs, and the survivor functions drop. Because not everyone leaves before data collection is over, the curves never reach zero.

All sample survivor functions have a similar shape—a negatively accelerating extinction curve, a monotonically nonincreasing function of time. The rate of decline, however, can differ across different types of teachers, and even small differences in these rates can yield large differences in aggregate career duration. For example, although the two sample survivor functions in the top panel of Figure 1 have similar shapes, the somewhat sharper decline among women suggests that, on average, they leave teaching more readily and consequently have shorter careers.

Inspection of sample survivor functions documents the lengths of teachers' careers in the aggregate. How can this evidence be consolidated in a single summary statistic? One way is to figure out how long the "average" teacher remains in the classroom. If we could eliminate censoring by collecting data until all the teachers left, we could estimate a mean career length. But, because data collection inevitably ends before everyone leaves, the existence of censored observations—teachers with unknown career lengths—complicates our computations. Even in the presence of censoring, however, we can usually estimate the median career length—the amount of time that passes until half the sample has left. This midpoint, defined straightforwardly as the time when the sample survivor function equals one half, is referred to as the estimated *median lifetime* in the survival analysis literature. Examining the top panel

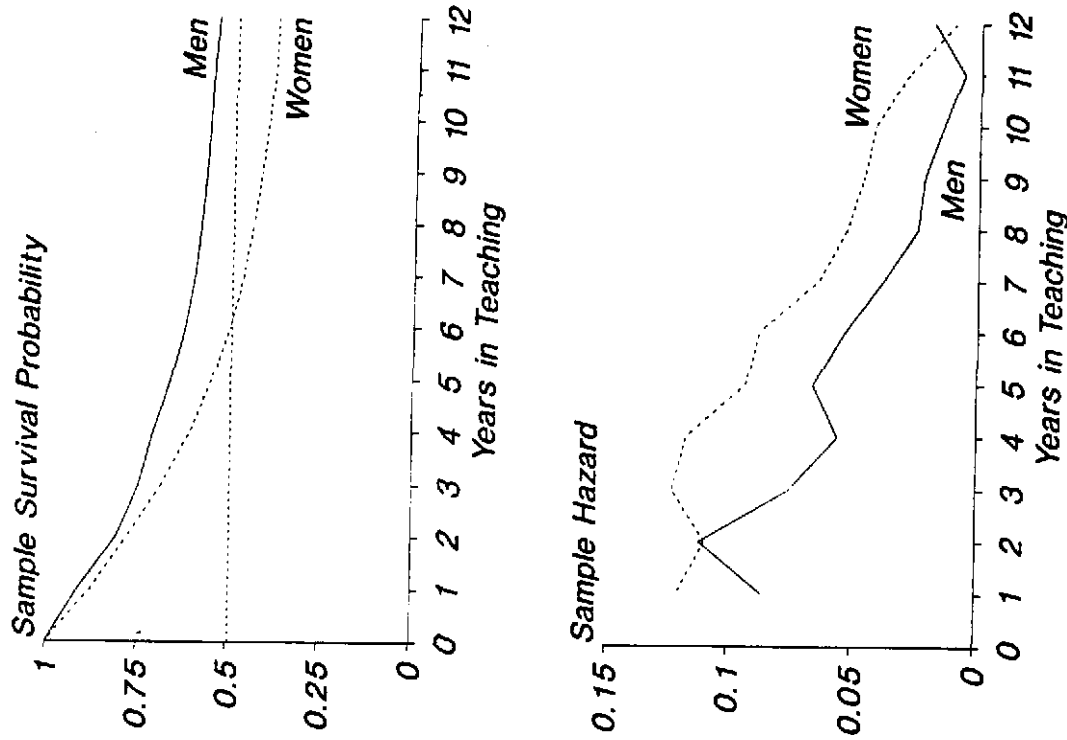


FIGURE 1. Sample survival probability and hazard plotted against years of teaching completed for 3,941 special educators hired in Michigan, by sex (based on Singer, 1992)

of Figure 1, we see that among this sample of special educators, the answer is: about 6 years for women and over 12 years for men. Because of the extreme censoring—more than half the male special educators are still teaching after 12 years—we cannot estimate their median lifetime precisely; all we know is that it exceeds 12 years.

The estimated median lifetime yields a descriptive answer to the "When?" question: How long does the average teacher teach? It evenhandedly summarizes the career lengths of a sample of teachers in the intuitively meaningful metric of time, pooling data from noncensored and censored cases together. Even when we cannot

compute a precise estimate of the median lifetime (as for the men in Figure 1), a lower bound is informative and certainly less biased than the estimates obtained by the ad hoc strategies mentioned earlier. Among these male and female special educators, for example, the highly discrepant estimated median lifetimes show how modest differences in survival probability translate into large differences in aggregate career duration.

Despite their appeal and popularity in the medical literature, estimated median lifetimes are rarely reported in the educational literature. We urge their use in research on educational milestones because we believe that they are a sensible summary statistic for the question at hand and because they facilitate communication with lay audiences and the comparison of findings across studies.

When Are Teachers Most Likely to Leave?

As informative as sample survivor functions and estimated median lifetimes are, they are simply cumulative longitudinal summaries of how many teachers remain in the classroom over time. Teachers cannot teach continuously through their fourth year unless they have also taught continuously through their first, second, and third years. So even each year's survival probability confounds information about leaving in that year with cumulative information about leaving in all preceding years. Cumulation inhibits identification of specific years of the career that are uniquely and separately risky; yet it is precisely this year-by-year information that we need to identify when teachers are most likely to leave.

How can we detect especially risky time periods? One way is to look for fluctuations in the slope of the sample survivor function. If the survivor function plunges sharply between one year and the next, this implies that a large proportion of those teachers still teaching at the end of one year left before the end of the next. Looking for such slope changes in the sample survivor functions in the top panel of Figure 1, we see that the early years on the job appear riskiest for both men and women, a finding replicated in almost every study of the teaching career (Charters, 1970; Grissmer & Kirby, 1987; Mark & Anderson, 1978, 1985; Murnane et al., 1988, 1989; Whitener, 1965).

Although examination of slope changes in sample survivor functions is a decent way to identify particularly risky time periods, researchers relying on visual approaches can inadvertently overlook potentially important variations in slope, especially in the more level sections of the survivor function. The survival analysis framework offers a more accurate mathematical tool—the hazard function—for detecting fluctuations in the survivor function's slope.

The computation of the sample hazard function is straightforward: for each year, identify the *risk set* (the pool of teachers still available to teach) and calculate the proportion of this group that leaves during the year. These estimated proportions are called sample *hazard probabilities*, and they indicate the conditional probability that a teacher will quit in that year, given that he or she survived through the end of the previous year. Collecting a sequence of hazard probabilities together as a plot over time provides the *hazard function*, a chronological summary of the risk of leaving teaching. By examining the sample hazard function and by comparing hazard probabilities for different years, we can pinpoint precisely when teachers are most likely to leave.

The lower panel of Figure 1 displays the sample hazard functions corresponding to the sample survivor functions in the upper panel. Among both men and women, the

risk of leaving teaching is highest during the first few years on the job and drops in subsequent years. Special educators are more likely to quit during their first few years on the job when they initially confront the daily demands of school life; those who survive this break-in period generally teach for years to come.

This pattern of declining risk is familiar to any school administrator. One of the first researchers to document it was Whitener (1965), who studied 937 suburban St. Louis teachers hired between 1951 and 1953. While 62% left within their first 5 years of teaching, only 25% of those who remained left within the next 5 years. As Whitener discovered, the advantage of computing hazard probabilities was that these statistics pinpoint when teachers are most likely to leave. A second advantage, not known at the time of Whitener's study, is that a focus on the hazard function facilitates the construction of statistical models that can be used to detect critical predictors of the career profile.

Identifying Important Predictors of When Teachers Are Most Likely to Leave Teaching

Estimated survivor functions, median lifetimes, and hazard functions persuasively describe when (and whether) a sample of teachers leaves teaching. Researchers have effectively used these descriptive statistics to answer questions about differences in career paths across groups. Grissmer and Kirby (1987) compared annual attrition rates among men and women of different ages, documenting the increase in attrition as teachers neared retirement. Heyns (1988) presented 5-year attrition rates by school type and location and concluded that teachers are more likely to leave good schools in good locations than problem schools in difficult locations. Singer and Willett (1988) explored systematic variation in hazard probabilities by entry cohort and uncovered career disruptions created by involuntary layoffs. Schlechty and Vance (1981) examined tables of estimated survivor functions for teachers with differing test scores to show that teachers with higher test scores are more likely to leave.

Each of these examples implicitly uses teacher and school district characteristics to predict variation in the career profile. When we examine the pair of sample survivor and hazard functions displayed in Figure 1, we, too, are implicitly treating teacher sex as a predictor of the career profile. But such descriptive comparisons are ultimately limited. How can we examine the effects of continuous predictors using such plots? How can we examine the effects of several predictors simultaneously or explore statistical interactions among predictors? How can we make inferences about the population from which the sample was drawn? As Grissmer and Kirby (1987) note, "merely disaggregating [attrition rates] across various subgroups of teachers may potentially lead to some erroneous policy conclusions" (p. 74). Under the survival analysis rubric, we overcome these limitations by fitting and testing statistical models of the hazard function.

Before we can introduce the required statistical models here, we must refine our definition of hazard, now distinguishing carefully between time measured in discrete intervals and time measured on a continuous scale. In the examples above, time has been measured discretely in years; we know only the intervals within which the events of interest occur. As we have stipulated already, discrete-time hazard is defined as the conditional probability that a teacher will leave during a particular time interval, given that he or she taught until the immediately prior interval. As a probability, the

computed value of discrete-time hazard must lie between 0 and 1. If we could measure time continuously, in contrast, we would know the particular instant when each teacher quit, and we would need to define hazard differently because the probability that any event occurs at a single "infinitely thin" instant of time tends to zero (by definition). Continuous-time hazard is redefined as the instantaneous rate of quitting at each time, given that the teacher has taught until the immediately prior instant. It can assume any value greater than, or equal to, zero. For a formal definition of the continuous-time hazard rate see Allison (1984), Kalbfleisch and Prentice (1980), or Miller (1981).

Researchers studying educational transitions usually measure time discretely because the events under study only occur, or are only assessed, at regular intervals—every week, month, semester, or, as in this example, year. For this reason, and for reasons of conceptual clarity, we assume the discrete case throughout this article.

Specifying a Statistical Model of the Hazard Profile

Statistical models of hazard express hypothesized population relationships between entire hazard profiles and one or more predictors. To motivate our representation of these models, examine the two sample hazard functions in the bottom panel of Figure 1 and think of the teacher's sex as a dummy variable, FEMALE, which can take on two values (0 for men, 1 for women). In this case, the entire hazard function is the conceptual outcome, and FEMALE is a potential predictor of that outcome.

Consider how the predictor affects the outcome. When FEMALE = 1, the sample hazard function is higher, relative to its location when FEMALE = 0. So conceptually, the predictor FEMALE somehow displaces or shifts one sample hazard profile vertically, relative to the other. A population hazard model formalizes this conceptualization by ascribing the vertical displacement to predictors in much the same way as an ordinary linear regression model ascribes differences in mean levels of any continuous noncensored outcome to predictors.

The difference between a hazard model and a linear regression model, of course, is that the entire hazard profile is no ordinary continuous outcome. The discrete time hazard profile is a set of conditional probabilities, each bounded by 0 and 1. Statisticians developing a model to represent any bounded outcome as a function of a weighted linear combination of predictors generally transform the outcome so that it is unbounded (Mosteller & Tukey, 1977). Transformation prevents derivation of fitted values that fall outside the range of theoretical possibilities—in this case, fitted probabilities less than 0 or greater than 1. When the outcome is a probability, as it is here, the logistic (or logit) transformation is mathematically and conceptually appealing. If p represents a probability, then $\text{logit}(p)$ is the natural logarithm of $p/(1-p)$; in the case of the teaching career, when p is a hazard probability, $\text{logit}(p)$ can be interpreted as the conditional log-odds of leaving teaching (Hanushek & Jackson, 1977).²

The effect of the logistic transformation on a hazard profile is illustrated in Figure 2, which presents sample logit-hazard functions corresponding to the plots in the bottom panel of Figure 1. The logistic transformation has its largest effect on proportions near 0 (or 1), expanding the distance between values at these extremes. In this figure, because the hazard probabilities are small (only a small proportion of the current teaching force leaves each year), the logistic transformation widens the gap between the two functions, especially in the later years.

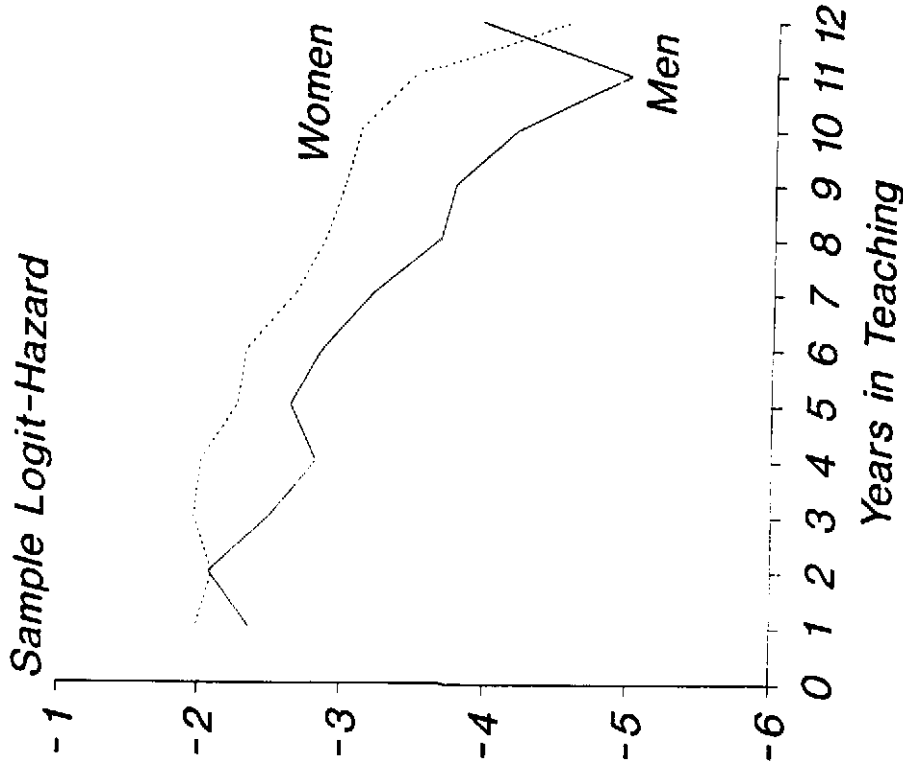


FIGURE 2. Sample logit-hazard versus years of teaching completed for the teachers whose survival and hazard functions are presented in Figure 1

Inspection of the sample relationship between the predictor FEMALE and the entire logit-hazard profile in Figure 2 suggests an appropriate format for population models of hazard as a function of predictors. When FEMALE = 1 (for women), the logit-hazard function is consistently higher, relative to its location when FEMALE = 0, indicating that in every year women are more likely to leave. So, ignoring any differences in the shapes of the profiles for the moment, the predictor FEMALE essentially displaces the logit-hazard profiles vertically, relative to each other.

Letting $h(t)$ represent the entire population hazard profile, a statistical model that captures this vertical displacement relates the logit transform of $h(t)$ to the predictor FEMALE as follows:

$$\text{logit } h(t) = \beta_0(t) + \beta_1 \text{FEMALE.} \quad (1)$$

The model parameter $\beta_0(t)$ is known as the *baseline logit-hazard profile*. It represents the value of the outcome (the entire logit-hazard profile) when the value of the predictor FEMALE is zero (i.e., it specifies the profile for men). We write the baseline as $\beta_0(t)$, a function of time, and not as β_0 , a single term unrelated to time (as in regression analysis), because the outcome (logit $h(t)$) is a temporal profile. The model specifies that differences in the value of the predictor shift the baseline logit-hazard profile up or down. The slope parameter, β_1 , captures the magnitude of this shift; it represents the vertical shift in logit-hazard associated with a one-unit difference in the predictor. Because the predictor in this example is a dichotomy, FEMALE, β_1 captures the differential risk of leaving for women over men. If the model were fitted to the sample data in Figure 1, the obtained estimate of β_1 would be positive because women are at a greater risk of leaving in every year.

The fitting of hazard models provides a powerful, flexible, and sensitive approach to the investigation of educational transitions that allows simultaneous inclusion of both censored and uncensored individuals. Even hazard models like Equation 1, which include only a single predictor, have proven useful for studying teachers' careers. A pioneer in this tradition was Charters (1970), who used an early variant of hazard models to explore sequentially the effects of sex, age, and grade-level taught on the career durations of 2,064 teachers newly hired in Oregon in 1962.

Although hazard models may appear strange at first, they do, in fact, resemble the more familiar multiple regression and analysis of variance models. The models can incorporate several predictors simultaneously by including them as linear (or nonlinear) functions of unknown parameters on the right-hand side of the equation. Such expansion allows examination of one predictor's effect while controlling statistically for others'. To examine the effect of a teacher's age at hire (AGEHIRE) after controlling for sex, for example, we would add a second predictor to the model in Equation 1 and write:

$$\text{logit } h(t) = \beta_0(t) + \beta_1 \text{FEMALE} + \beta_2 \text{AGEHIRE}. \quad (2)$$

The parameter β_2 assesses the difference in the elevation of the logit-hazard profile for two teachers whose ages are 1 year apart at hire, controlling for sex. If β_2 were negative, teachers who were older when hired would be less likely to leave in every year of their careers; if β_2 were positive, the reverse would hold.

We examine the synergistic effect of several predictors by including statistical interactions in hazard models. All we do is add appropriate cross-product terms to main effects models in much the same way we do when examining interactions in multiple regression models. We would explore whether the effect of a teacher's age at hire differed by sex by modifying Equation 2 as follows:

$$\text{logit } h(t) = \beta_0(t) + \beta_1 \text{FEMALE} + \beta_2 \text{AGEHIRE} + \beta_3 \text{FEMALE*AGEHIRE}, \quad (3)$$

and examining the magnitude and direction of an estimate of the parameter β_3 . By investigating such two-way interactions, Murnane et al. (1991) showed that women who were younger than 30 years when hired were more likely to leave their teaching jobs than were either older women or men of any age.

One important additional advantage of hazard models is the ease with which they can include two distinct types of predictors: those whose values are constant over time and those whose values vary over time. As befits their label, *time-invariant predictors* describe immutable characteristics of people and their jobs—such as, their

sex, race, and licensing examination score. The values of *time-varying predictors*, in contrast, may fluctuate with time, as might a teacher's salary, job assignment, marital status, or job conditions. Time-varying predictors are distinguished by the presence of a parenthetical t in the variable name.

The inclusion of time-varying salary (in thousands of dollars, corrected for inflation) in the hazard model in Equation 3, for instance, permits us to ask whether teachers who are paid more are at a lesser risk of leaving teaching:

$$\text{logit } h(t) = \beta_0(t) + \beta_1 \text{FEMALE} + \beta_2 \text{AGEHIRE} + \beta_3 \text{FEMALE*AGEHIRE} + \beta_4 \text{SALARY}(t). \quad (4)$$

In Equation 4, we hypothesize that the logit-hazard profile depends on three time-invariant and one time-varying predictor. In this model, although a teacher's salary fluctuates with time, its per-thousand dollar effect on the risk of leaving teaching is constant over time and is represented by the single parameter β_4 . If β_4 is negative, more highly paid teachers are less likely to leave their jobs.

We believe that the ease with which time-varying predictors can be incorporated into hazards models offers researchers an innovative and powerful analytic opportunity. Many potentially important predictors of teachers' career paths—salary, teaching assignment, and school and classroom climate—fluctuate naturally with time. In traditional analyses, temporal fluctuation in the values of the predictors has been well nigh impossible to handle. With the advent of hazard modeling, this is no longer the case. We are convinced that the inclusion of time-varying predictors in survival analyses will dispel many of the myths and mysteries surrounding teachers' professional lives. By including time-varying salary as a predictor in their survival analyses, for example, Murnane et al. (1989, 1991) and Murnane and Olsen (1989, 1990) provide clear evidence that better paid teachers stay in the classroom longer.

Because of the lack of statistical methods that permit the incorporation of time-varying predictors, most quantitative research to date has emphasized easily measured time-invariant predictors—such as, age at hire, year of hire, sex, entering score on the National Teacher's Examination. Much more will be learned when time-varying predictors are explored. Case studies of teachers' careers suggest that class assignments, personal attitudes towards the job, and relationships with administrators may influence career decisions more than simple demographics (Farber, 1991; Johnson, 1990; Lortie, 1975). Quantitative study of such effects has been difficult because these characteristics fluctuate over time. Once-satisfied teachers become dissatisfied. Teachers who had easy classes are given difficult and demanding ones. The student body changes. The salary schedule becomes less competitive. A new principal is hired. Without the ability to include time-varying predictors in the statistical model, quantifying such effects was simply beyond a researcher's grasp.

With the advent of hazard models and computer software for fitting them, the effects of both types of predictors can be explored. We especially encourage researchers conducting longitudinal studies to collect data on time-varying predictors that describe teachers' experiences in school. Whereas such data collection was once perhaps futile (without methods for exploiting the data), this is not the case any more. We reiterate Chapman's (1983) advice of nearly a decade ago: The study of the teaching career must move beyond the analysis of demographic data; we must turn to the teachers themselves and their lives in school to learn why they make the career decisions they do.

Interpreting the Parameters of a Hazard Model

Discussion of methods for estimating the parameters of hazard models, evaluating their goodness of fit, and making inferences about the population based on sample data are beyond the scope of this article. A variety of statistical methods is available, differing in their assumptions about the underlying distribution of risk in the population and their ability to handle predictors of different types. Readers seeking information about model fitting, estimation, inference, or computer software should consult one of the references identified in the Appendix.

Once the parameters of a hazard model have been estimated, they can be reported along with standard errors and accompanying model goodness-of-fit statistics in much the same way that the results of multiple regression analyses are reported (Allison, 1982; 1984). Singer and Willett (1991) provide a nontechnical review and comment on the approaches that have been used to report and interpret such statistics.

Because one good picture is worth a thousand words (or numbers), graphics rather than tables of parameter estimates can easily and powerfully summarize analytic findings. Just as researchers who have used multiple regression analysis can present systems of fitted regression lines to display the influence of statistically significant and substantively important predictors, so, too, can researchers who have used survival methods present predicted survivor and hazard functions computed for prototypical teachers—teachers who share specific values of critical predictors. Examples of this approach can be found in Murnane et al. (1988, 1989, 1991) and Singer (1992).

We illustrate this approach in Figure 3, which presents the results of fitting the model posited in Equation 3 to the Michigan special educator data introduced in Figure 1. In this model, age at hire was recoded as a dichotomy (0 when teachers were 30 years old or younger when they began teaching, 1 when they were older than 30) because preliminary analyses supported the superiority of this specification.

These fitted plots provide clear answers to the original research question about when teachers leave the schools; in the process, they also answer the related question about whether certain demographic groups are more likely to leave. Although the first years in teaching are riskiest for everyone, women under 30 are especially likely to leave. In every year of the teaching career, the risk of leaving is nearly twice as high for these women. The fitted survivor functions and estimated median lifetimes in the bottom panel of Figure 3 document the cumulative effects of these divergent annual risks. Young women have an estimated median lifetime of about 6 years, while the survivor functions for the other three groups remain above 50% even after 12 years, precluding estimation of precise median lifetimes.

Despite the roundabout path from research question to research finding—from event times, through sample survivor and hazard functions, to fitted models of the risk profile—graphic displays close the analytic circle in a meaningful fashion. Fitted hazard and survivor functions for specific values of predictors summarize the temporal fluctuations in risk. And the median lifetime statistic, estimated from the fitted survivor functions, provides a single number summary of the career for important subgroups.

What If the Effects of the Predictors Change Over Time?

When processes evolve dynamically, the effects of predictors may vary over time, changing from week to week, month to month, or year to year. A predictor whose effect is constant over time has the same impact for new and experienced teachers

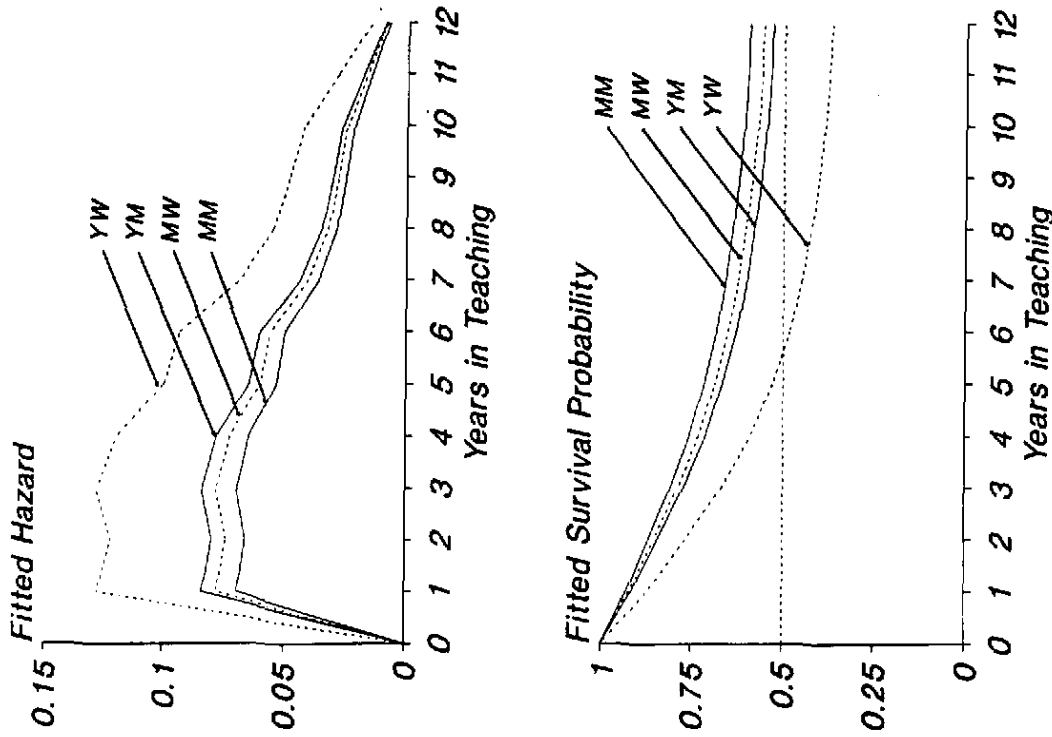


FIGURE 3. Fitted hazard and survivor functions for teachers in four demographic groups (young women, young men, mature women, and mature men)

alike. A predictor whose effect varies over time, in contrast, has a different impact on hazard in each year of the career. In the previous section, we distinguish between two types of predictors: (a) time-invariant predictors—whose values do not change over time (i.e., sex)—and (b) time-varying predictors—whose values may change over time (i.e., Salary). Now we consider a completely different distinction by contrasting two types of effects. Both time-invariant and time-varying predictors may have effects that either are constant or vary over time.

Even time-varying predictors can have time-invariant effects. Consider the effects

of teacher salary on the risk of leaving teaching. Salary is a time-varying predictor—its dollar value changes over time (even after adjustment for inflation)—but its effect can be constant over time, or it may vary over time. If the effect of salary is time-invariant, an extra \$1,000 per year is an identical inducement to both experienced and novice teachers. If the effect of salary varies over time, in contrast, an extra \$1,000 might have a bigger effect for novices.

The four hazard models posited so far have purposefully ignored the option that a predictor's effect may vary with time. They have neglected the very real possibility that salaries might be more important for novices than for veterans. Yet a predictor's effect may indeed vary over time. By decreasing attrition among those most likely to leave (beginning teachers), for example, an extra few thousand dollars in the first year could ultimately double the length of teachers' careers.

Hazard models in which predictors have time-invariant effects have a special property: In every year (t) under consideration, the effect of the predictor on the risk of leaving teaching is exactly the same. In Equation 1, for example, the magnitude of the vertical shift in the logit-hazard profile for women is always β_1 . One implication of this identical-shift-at-all-times feature is that the logit-hazard profiles for men and women have identical shapes, because their profiles are simply shifted versions of each other. Generally, in these models, the entire family of logit-hazard profiles represented by all possible values of the predictors shares a common shape and is mutually parallel, differing only in relative elevation.

In the parlance of survival analysis, such models are called proportional-hazards models. The terminology arises from what we see when we examine displacements of the original hazard profiles in their untransformed scale. If the logit-hazard profiles are parallel, the corresponding raw hazard profiles are simply magnifications and diminutions of each other—they are proportional. Because the model in Equation 3 includes predictors with time-constant effects, the proportional-hazards assumption has been imposed, and the four, fitted hazard functions in Figure 3 do indeed have the required magnified, or diminished, proportional profiles.³ Singer and Willett (1991) draw an analogy between the proportional-hazards assumption and the assumption of homogeneity of regression slopes in the analysis of covariance (see also, Willett & Singer, 1988).

Proportional-hazards models are probably the most popular type of hazard model being used in empirical research today. In the job turnover literature, they have been used to analyze data describing the behavior of diverse groups of workers ranging from university professors (Rosenfeld & Jones, 1987) and Air Force cadets (Morita, Lee, & Mowday, 1989; Mowday & Lee, 1986) to retail store employees (Darden, Hampton, & Boatwright, 1987) and adolescents entering the labor market (Johnson & Herring, 1989). This boom is being fueled, in part, by the increasing availability of prepackaged mainframe and personal computer routines for fitting these models (see the Appendix).

But is it sensible to assume that the effects of predictors are unilaterally time-constant and that all hazard profiles are magnifications and diminutions of each other? Does the proportional-hazards assumption really hold in practice? Recent research on teachers' careers leads us to believe that "No" is the answer to these questions—that the proportional-hazards assumption may fail in substantively interesting ways (Murnane et al., 1989, 1991; Singer, 1992). In sample after sample, among teachers of different subjects and in different states, these researchers have found that many predictors do more than simply displace the logit-hazard profile.

They also alter its shape. Even in Figure 2, for example, the sample hazard profiles for men and women are neither magnifications nor diminutions of each other.

If the effect of a predictor varies over time, we must specify a nonproportional hazard model that allows the shapes of the logit-hazard profiles to differ. As in multiple regression analysis, when the effect of one predictor differs by the levels of another, we say that the two predictors interact; in this case, we say that the predictor interacts with time. In Figures 1 and 2, the sex differential in logit-hazard fluctuates from year to year, suggesting that sex and time might interact in the prediction of logit-hazard. To test this conjecture, all we need do is include the cross product of that predictor and time as an additional predictor in the model.

Predictors that interact with time have interesting interpretations, reflecting complex and fluctuating relationships between predictors and risk. Some predictors primarily affect early hazard. In their investigation of North Carolina teachers, Murnane et al. (1989, Fig. 2) show that the effect of salary decreases over time: It is large among new teachers and virtually disappears by the eighth year. Other predictors primarily affect late hazards. When the effect of a predictor emerges over time, initially coincident hazard profiles diverge. Singer and Willett (1991) show, for example, that fitted hazard functions for Michigan special educators hired before and after 1975 (the year in which the Education for All Handicapped Children Act, Public Law [PL] 94-142, was passed) virtually coincide in the first 5 years and diverge thereafter, with the hazards for pre-PL 94-142 teachers remaining slightly higher.

When a predictor interacts with time, as many do, proportional hazards models do not reflect reality. Nonproportional hazards models are becoming increasingly popular, because, in discrete-time, they easily can be fit using standard logistic regression software (Singer & Willett, in press; Willett & Singer, 1991). Readers interested in estimating the parameters of nonproportional-hazards models, evaluating their goodness of fit, and making inferences about populations based on sample data should consult the references catalogued in the Appendix.

Distinguishing Between Teacher Transfers and Voluntary Versus Involuntary Attrition

Not all teachers who leave their school districts stop teaching altogether. Not all teachers who stop teaching altogether do so voluntarily. Teaching spells can end in different ways; in any particular time period, one path may predominate. When the local economy is booming and educators are under fire, teachers may quit and seek private sector opportunities. When suburban enrollments are rising, transfers may be popular as teachers seek jobs closer to home. When enrollments are falling, layoffs and reductions in force may be common. In some jurisdictions, all three processes may co-occur if the private sector needs employees with specific skills, while the schools need teachers of some subjects but not others.

Despite the presence of competing exit routes from the profession, each teacher can end any given teaching spell in one, and only one, way. Focusing on voluntary versus involuntary terminations, for example, we see that teachers who are fired cannot also quit; teachers who quit cannot then be fired. These two events (quitting and firing) compete with each other to end a teacher's career—once a teaching spell ends for one reason, it cannot later end for another. Leaving, for either reason, prevents a teacher from leaving for the other reason; once she leaves, she is no longer at risk.

The presence of multiple competing exit routes complicates, but it does not invalidate, survival analysis. Competing risks survival analysis is a straightforward extension that permits the study of the natural complexities of the teaching career.

Predictors associated with each competing risk can be identified. This allows the construction of competing risks hazard models in which the risk of layoff might depend on a teacher's year of hire (Singer & Willitt, 1988) while the risk of voluntarily quitting for jobs outside of education might depend on a teacher's subject specialty (Murnane et al., 1988) and the risk of retirement might depend on a teacher's age (Berry, 1988).

Perhaps the greatest problem in conducting a competing risks survival analysis involves identifying which competing risk actually was responsible for ending each teacher's career. Teachers anticipating a layoff or tenure denial may quit voluntarily rather than wait for the inevitable. If the events can be distinguished, however, the analysis is straightforward. The researcher builds as many hazard models as there are competing events, using a different definition of censoring in each analysis. The general principle is that, when studying any particular event, a teacher's data record is censored at the end of data collection (if she never left) or at the time of exit if she left for any reason other than the particular event being modeled. When examining voluntary termination, for example, teachers who were laid off are censored at the date of layoff because leaving, even involuntarily, eliminates the risk of voluntary termination. When modeling involuntary termination, teachers who quit of their own volition are censored at time of quitting. The censoring indicators in competing risks survival analysis are set prematurely early whenever any transition other than the one of interest occurs. Allison (1984) provides further details.

Competing risks survival analysis was used effectively by Title (1990), who modeled the risk of leaving a school district by either transferring to another district in the state or not teaching in the state altogether. By modeling these two competing risks, Title showed that, while the risk of leaving teaching altogether declined over time, the risk of switching districts increased. Competing risks survival analysis holds great promise for the study of teacher careers, especially if researchers can interview the teachers at termination to determine precisely why they left. As Theobald (1990) notes,

a teacher's decision to continue teaching in the same school district in which s/he is currently employed or to pursue alternative opportunities, which may include transferring to a different district or leaving the public school sector . . . is the definition of attrition which is of most consequence to school district policy-makers. (p. 242)

Returning Teachers

Many teachers who quit teaching eventually return. The National Education Association (1987) estimates that more than 80% of the teachers newly hired by the nation's public schools in 1986 were certified teachers who either were not in school or who had not taught the previous year (the reserve pool). Recent research by the State Departments of Education in Connecticut and New York highlights the importance of the reserve pool and the inevitability of second and subsequent teaching spells; 60%–70% of recently hired teachers in these states were members of the reserve pool (Connecticut Department of Education, 1987; Murnane et al., 1989). Whereas many members of the reserve pool may not have yet taught, many others are indeed former teachers who have taken a break from teaching (Heyns, 1988; Murnane et al., 1991; Theobald, 1987).

Research questions about whether teachers reenter the teaching profession can be answered by using survival methods to discover when they are likely to return. As in the case of the "first teaching spell," although some researchers simply model

whether teachers returned during a finite time period (e.g., see Heyns, 1988, and Murnane et al., 1988), a better method is to build hazard models of the risk of re-entry.

The idea is simple: Instead of exploring the time in the profession, researchers should explore the time out of the profession. All that is required is a representative sample of teachers who have left the schools. Summary statistics, statistical models, and estimation methods are identical. Teachers who do not return before data collection ends have censored return times. Murnane et al. (1991) used this strategy to show that the risk of reentry is highest in the year immediately after leaving. They found that 1 in 6 teachers who left Michigan and North Carolina public schools returned after only 1 year; among those who stayed out for a second year, 1 in 20 returned the next.

After modeling the risk of reentry, a researcher can then separately model the length of second and subsequent teaching spells. This modeling of the time in, and time out of, the classroom can be repeated as many times as necessary. By separately modeling each individual spell, a researcher can determine whether career paths of returning teachers differ from career paths of first-time teachers. We believe that building a taxonomy of such models holds the key to understanding fully why teachers leave the schools and why they return.

Is Survival Analysis Really Necessary?

We briefly return now to our main thesis—that researchers studying whether events occur should do so by using survival analysis to model when events occur. We raise this issue again because we believe that the use of a complex statistical method requires justification. Why bother with complexity if an equally valid answer can be extracted from the same data using simpler methods? In this section, building on principles introduced in previous sections, we describe four ways in which traditional analytic methods can obscure important information about the occurrence of events, information that is sensitively and assuredly revealed by methods available within the survival analysis framework.

First, answers obtained by researchers using traditional methods are inextricably linked to the particular time frame chosen for data collection and analysis; yet, in studies of the teaching career, these time frames are rarely substantively motivated. Researchers comparing 1-year, 5-year, or 10-year attrition rates for men and women or high- and low-testing teachers, for example, are simply describing cumulative differences in behavior until these times. All other variation over time in the rate of leaving is lost. The literature is filled with examples of disparate risk profiles that lead to comparable attrition rates at specific points in time (e.g., see Mark & Anderson, 1978, Table 1; Schlechty & Vance, 1981, Tables 2 and 3). Just because two groups of teachers have identical attrition rates at one point in time does not mean that they followed similar trajectories to get there—most of those in one group might have left in the first year while those in the other might have been equally likely to leave at all points in time. The 1-year, 5-year, and 10-year cutpoints used in the past are convenient but not purposeful. By documenting variation in risk over time and by discovering what predicts variation in risk, we can better understand why teachers leave teaching. Traditional methods disregard this information; with survival methods, variation in risk becomes the primary analytic focus.

Disregard for variation in risk over time leads to a second problem with traditional methods; contradictory conclusions can result from nothing more than variations in

the particular time frames studied. Had Schlechty and Vance (1981) computed 1-year, 3-year, or 5-year attrition rates when studying the career paths of Black teachers hired in North Carolina in 1974, for example, they would have reached three seemingly discrepant conclusions: The 1-year rates would have shown that women stay longer; the 3-year rates would have shown no difference, and the 5-year rates would have shown that men stay longer. By thoughtfully presenting survivor functions, they showed that men were more likely to leave in the first year but women were more likely to leave in each of the next six. Researchers using traditional methods must constantly remind themselves that conclusions can change as the time frame changes. While such caveats usually appear in the "Results" section of an article, they often disappear by the "Discussion" section. In survival analysis, the time frame itself is an integral part of the answer; it highlights, rather than obscures, variation over time.

Third, traditional analytic methods offer no systematic mechanism for incorporating censored observations into the analyses. If all the teachers under study are followed for the same length of time, researchers typically collapse them into two groups: those who left before the end of data collection (the censoring point) and those who did not. Chapman (1984), for example, compared teachers who taught continuously for 5 years with those who left before 5 years. But if the first year on the job is the hardest, teachers who leave in the first year may differ systematically from those who leave subsequently. Dichotomization conceals such differences; survival methods, which focus on the risk of leaving teaching in each year of the career, bring such differences to light.

If the teachers under study are followed for different lengths of time (as when researchers follow cohorts of teachers hired in each of several successive years until a single fixed point in time), traditional methods falter. This may explain why researchers in this analytic predicament have pioneered the application of survival methods (e.g., Charters, 1970; Mark & Anderson, 1978, 1985; Schlechty & Vance, 1981; Whitener, 1965), while those able to maintain a constant censoring time have favored more traditional approaches (e.g., Chapman, 1984; Heyns, 1988). If censoring times vary across people, the risk periods vary as well. People followed for longer periods of time have more opportunities to leave than do those followed for shorter periods of time. So observed differences in attrition rates might be attributable to nothing more than research design. Although we can equate risk periods by discarding data describing behavior that occurred after the earliest censoring point, why set aside data already collected? With survival analysis, each person is censored at the particular time that his or her data record ends, and all of the obtained data is used in the analyses; censoring times need not be identical for everyone under study. With traditional methods, a researcher must develop his or her own strategy for handling censoring.

Fourth, traditional analytic methods offer few mechanisms for including predictors whose values vary over time or for permitting the effects of predictors to fluctuate over time. To overcome this limitation, researchers studying the effects of variables such as salary and job satisfaction tend to use predictor values corresponding to a single point in time, the average of values over time, or the rate of change in values over time. This is not the case in survival analysis. The analytic effort is identical whether including predictors that are static over time or predictors that change over time; so, too, it is easy to determine whether the effects of predictors are constant

over time or whether they differ over time. There is no need to create a single-number summary of the temporal behavior of a changing predictor. Traditional methods force researchers into building static models of dynamic processes; survival methods allow researchers to model dynamic processes dynamically.

For all these reasons, we believe that researchers studying whether events occur should investigate the possibilities offered by survival methods. In the recent past, when these methods were in their infancy and statistical software was either not available or not user friendly, researchers reasonably adopted other approaches. But experience elsewhere in the social sciences shows that these methods, originally developed to model an event seemingly beyond a person's control (death), lend themselves naturally to the study of individual behavior. While software lags behind, this is an area of active research with rapidly improving options (see Appendix; Goldstein, Anderson, Ash, Craig, Harrington, & Pagano, 1989). The time has come for educational researchers modeling the occurrence of events to explore the utility of survival methods. In the hopes of encouraging this movement, we now consider another substantive topic that lends itself naturally to these methods—the timing of student dropout and graduation.

Research on Student Dropout and Graduation

Educational administrators, policymakers, and society at large share a deep concern that too many students drop out of school before completing their degrees (Caterall, 1987; Levin, 1972). The problem occurs at every junction of the educational pipeline; too many students drop out of high school (Natriello, 1987; Weis, Farrar, & Petrie, 1989), too many students drop out of college (Porter, 1990; Tinto, 1987), too many students drop out of graduate school (Maher, 1990; Zjolowski, 1990). And the concern is not just with American schools; similar issues arise in Canada (Watson, 1974), the United Kingdom (Buckley & Hooley, 1988; Johns & Taylor, 1989), Germany (Blossfeld, 1990), and elsewhere.

In this section, building on our discussion of methods for analyzing teacher career data, we show that survival methods are equally useful for analyzing student career data. By constructing hazard models of students' careers, we can investigate not only whether students drop out but also when they are most likely to do so. The models can be used to study the risk of leaving high school, college, or graduate school, and they lend themselves to a variety of substantive questions. We can use them to ask: (a) Are students more at risk of leaving during particular stages of their careers? (e.g., during the last year of high school or the first year of college); (b) does the profile of risk differ across groups? (e.g., are girls less likely to drop out than boys?); and (c) do particular policies and programs have an impact? (e.g., are students enrolled in support programs less likely to drop out?).

As Bean (1980, 1983) argues, the study of student careers is similar to the study of teacher careers. But survival methods offer educational researchers much more than just a sophisticated data analytic approach—they offer a unified framework for appropriately modeling the many paths real students take through real schools. Student careers can end in one of several ways; dropping out and graduating are just the most frequently studied events. Yet even these two events are hardly equivalent ways of leaving; each is a distinct risk that competes to end a student's career. Researchers want to identify the factors associated with both of these ends: (a) Whether (and when) students drop out and why, and (b) whether (and when)

students graduate and why. Survival analysis, particularly competing risks survival analysis, is a powerful way of answering all of these questions at the same time. Of course, many students take other paths through school. Some students neither graduate nor dropout; they stop out and return. And not all permanent dropouts leave in the same way; some leave voluntarily; some are expelled; some cannot complete the academic requirements, and others transfer, completing their degrees elsewhere. A complex network of interlocking risks competes to end students' careers in school. As Finn (1991) notes, "dropping out is not the simplistic 'now I'm here—now I'm not' phenomenon assumed (by default) in research that compares those who graduate with those who do not" (p. 29). With competing risks survival analysis, any number of qualitatively different modes of exit can be modeled. By building hazard models of each of these events, we can understand better the different forces that drive different students to different ends.

We begin our discussion of methods for studying students' careers by examining approaches developed over the years to study only one of these events—dropout. As we illustrated when reviewing methods used to study teachers' careers, we will show that many researchers—although perhaps unaware of the formal principals of survival analysis—have engineered sensible strategies for describing, summarizing, and drawing inferences from dropout data. Placing their contributions within a survival analysis framework helps us develop a unified approach to answering questions about the "Whether?" and "When?" not only of dropout (in all of its guises) but also of graduation, stop-out, and other transitions at the high-school, college, and post-graduate levels.

Retrospective Studies

Many researchers use retrospective information collected on a sample of people in one or more age cohorts to compute a dropout rate. For example, defining a high-school dropout as someone who neither has a diploma nor is currently enrolled in school, the U.S. Census Bureau estimates that 13% to 14% of people between the ages of 16 and 24 have dropped out of high school (U.S. Census Bureau, 1988, 1989). Across the general population, this proportion has remained fairly steady over the past 15 years (GAO, 1986), but for certain subgroups of people—particularly, people of color—it has been increasing over time (McDill, Natriello, & Pallas, 1985, 1986).

Although useful for describing secular trends, retrospective aggregate summaries have several limitations: (a) They pool disparate groups of people, and this lack of differentiation precludes subsequent detailed analysis (Fraser, 1989; Kominski, 1990); (b) they can exclude entire subgroups of the population, such as those who have died prior to data collection or those in the military (GAO, 1986); (c) they can be biased if respondents inflate their educational attainment levels, claiming to have graduated when in fact they have not (Rumberger, 1987); and (d) they rarely distinguish between GED certificates and high-school diplomas (Kolstad & Owings, 1986).

Whereas some of these problems can be resolved through improved data collection (e.g., see Blackorby, Edgar, & Korterling, 1991), survival analysis principles suggest that retrospective summaries of student career data have two further limitations: (a) They ignore the problem of censoring, assuming that people who have dropped out will never graduate and that people who have not graduated must be dropouts; and (b) they ignore when people dropped out. As Pallas (1986) points out when reviewing

studies of secondary school students and Terenzini (1987) points out when reviewing studies of college students, both of these are serious problems. Students who have dropped out may return to complete their studies; students who have not graduated may be continuing to work towards graduation. So, too, may information about the timing of dropout be informative, allowing researchers to identify periods of time in students' careers that demand more attention and the application of greater resources and effort. For these reasons, we urge researchers studying students' careers to avoid the use of retrospective data whenever possible.

Two-Wave Prospective Studies

The limitations of retrospective data have led many researchers to study students' careers prospectively. Analyses using two waves of data, separated by a single semester or academic year, are especially popular. Many states and school districts, for example, routinely calculate annual dropout rates for students just as they routinely calculate annual attrition rates for teachers (e.g., Massachusetts Board of Education, 1990). So, too, do higher education researchers; although at the postsecondary level, there is much greater variation in the length of time between the data collection waves (e.g., see Bean & Metzner, 1985; Murdock, 1987).

The most popular prospective two-wave approach is to compare total enrollments across time, either across or within grades. At the high-school level, for example, a 10th-grade dropout rate would be calculated by comparing one year's 10th-grade enrollment to the next year's 11th-grade enrollment. Despite their popularity, dropout rates calculated using aggregate enrollment figures are among the most misleading educational statistics published today. Their purpose is often political, and they rarely provide insight into who drops out, when, or why (Mann, 1986). They do not account for the diverse paths students take through schools, transferring from one school to another (Fine, 1986; Morrow, 1986), stopping out temporarily but eventually returning (Finn, 1987), or leaving in one year to earn a GED later (Kolstad & Owings, 1986). And changing the subset of grades that comprise the base population can alter the dropout rate (Hammack, 1986; Morrow, 1986). Districts that want low rates can include the elementary grades; districts that want high rates can focus on the high-school years. Year-to-year comparison of aggregate enrollment statistics cannot accurately characterize students' paths through school and therefore should not be used to study dropout and graduation patterns.

In recent years, many reviewers of the student dropout literature have argued convincingly that researchers should use a superior two-wave approach—follow individual students over the academic year (e.g., Ewell, 1987; Frase, 1989; Pallas, 1986; Rumberger, 1987). Comparison of fall and spring records for each student, for example, permits calculation of an annual attrition rate—the proportion of students enrolled in a specific school (or school district) who leave during the year. LeCompte and Goebel (1987) show, however, that even these calculations are not without problems. For example, it can be especially difficult to define precisely each student's enrollment status at each particular point in time (Hammack, 1986; Morrow, 1986).

The principles of survival analysis, which introduce the necessity of ascribing risk to specific periods of time, highlight a further flaw in the computation of annual attrition rates—the masking of potentially important effects that can arise when data are combined across grades. As Hammack (1986) notes, many school districts compute annual attrition rates by pooling information across some or all of their

grades. Morrow (1986, Figs. 2a and 2b) provides a compelling example of the effects of this practice on attrition rate calculations. In Table 1, we use survival analysis principles to extend Morrow's example and show why we believe that dropout rates should never be based on data pooled across grades. Although these data are hypothetical, they clarify the need for researchers to move beyond calculation of simple annual attrition rates.

Table 1 presents the distribution of 64,106 students across grades K-12 in a single year in a hypothetical school district. The last two columns present the number of students who dropped out during the year and the consequent dropout rate. Focus, first, on the last three rows, which present dropout rates for three different combinations of grades. Across all grades, 3,307 students quit school during the academic year, yielding a dropout rate of 5%. Morrow shows how this rate changes as the reference group is modified. Restricting the base population to grades 7-12 increases the dropout rate to 12%. Restricting the base population to grades 9-12 increases it yet again, to 20%.

Survival analysis principles suggest that a grade-by-grade profile of the yearly risk of dropout might be more informative. We present such a profile in the fourth column of Table 1, which displays the proportion of students in each grade who drop out during the year. Akin to estimates of the hazard probability for each grade, these summaries document the substantial variation in dropout rates across grades. The annual dropout rate for students in K-7th grade is under 1% in every grade; it remains low in 8th and 9th grade, peaks in 10th grade, and drops slightly in 11th and 12th grade.

Grade-specific dropout rates are superior to pooled dropout rates because a complex longitudinal time-dependent process cannot be adequately summarized by a single statistic. Grade-specific rates precisely identify when students are at greatest

TABLE 1
Computation of a grade-specific annual dropout rate

Grade	Number of students	Number of dropouts	Dropout rate
K	5,422	10	.0018
1	5,422	26	.0048
2	5,422	11	.0020
3	5,422	9	.0017
4	5,422	5	.0009
5	5,422	4	.0007
6	5,422	12	.0022
7	5,198	46	.0088
8	5,197	89	.0171
9	5,108	286	.0560
10	4,822	1,501	.3113
11	3,321	815	.2454
12	2,506	493	.1967
K-12	64,106	3,307	.0516
7-12	26,152	3,230	.1235
9-12	15,757	3,095	.1964

Note. Adapted from Morrow, 1986, Figures 2a and 2b.

risk of dropping out. The notion of studying the timing of student attrition is hardly new. Many studies conducted in the 1950s and 1960s focused on the timing of attrition from high school (Bachman, Green, & Wirtanen, 1971; Cervantes, 1965; Coombs & Cooley, 1968; New York State Education Department, 1963) and college (Ifert, 1957; Sexton, 1965; Sharp & Kirk, 1974; Summerskill, 1962). By identifying precisely when students are at greater risk of dropping out, educational institutions can better target their dropout prevention resources. If dropout rates are high in freshman year, for example, schools should ask what happens to entering students that leads so many of them to quit. It is not enough to target students at high risk; those at high risk must be reached at the right time.

Multiwave Studies

Just as researchers studying teacher careers have moved away from two-wave studies, so, too, have researchers studying student careers. The need for multiwave data is clear. Estimating a list of grade-specific annual dropout rates, as in Table 1, improves on an aggregate two-wave approach but can be deceptive because each grade's annual dropout rate is based on a different cohort of students. If the demographic and social composition of the school (or school district) is changing over time (as it likely is), the all important grade (age) effects will be confounded with cohort (year of entry) effects (Baltes, 1968; Hogan, 1984; Schaie, 1965).

Confounding of cohort and grade effects can be avoided through judicious research design and data analysis. Instead of following several cohorts of students for a single year, a single cohort of students may be followed for several years. This multiwave approach, known as a *cohort approach* (Fraser, 1989), a *cumulative approach* (National Educational Association, 1965), a *holding power approach* (New York State Education Department, 1963), or a *panel approach* (Terenzi, 1982) is becoming increasingly popular. Researchers adopting this strategy follow groups of students who share a common initial status until an expected date of graduation and sometimes longer. Most studies, such as the 1982, 1984, and 1986 follow-ups of the High School and Beyond 1980 sophomore cohort, follow students who initially share a common grade in school (Appelbaum & Dent, 1988; Peng, Feiters, & Kolstad, 1981); others, such as the on-going annual follow-ups of the National Longitudinal Survey of Youth (NLSY), follow people who share a common birth year (Center for Human Resource Research, 1988).

Researchers with access to multiwave data can use the full array of survival methods to describe students' careers. The temporal profile of dropout risk can be characterized using the same statistics that we used to characterize multiwave data on teachers' careers—the survivor function, the estimated median lifetime, and the hazard function. Statistical models of hazard can be constructed to represent the relationships between the profile of grade-by-grade dropout risks and characteristics of the students, their experiences in school, and their lives at home.

Despite the natural application, survival methods have yet to be applied routinely to multiwave student career data. Investigators have instead asked whether students drop out by a particular time, usually the time that students are "expected" to have graduated. This narrower focus is a consequence of the existence of normative trajectories through school. Instead of characterizing what happens to students at each critical juncture (semester or year), there is a natural inclination to emphasize the "agreed-upon" time of the end-product—dropout or graduation by the 12th grade of high school or the 4th year of college.

End-product statistics can be informative and compelling. Using data collected as part of the 1982 follow-up of the 1980 sophomore cohort of High School and Beyond, for example, the National Center for Education Statistics (Fraser, 1989) estimates that by spring, 1982, when these students "should" have graduated, 74% had done so, 14% had dropped out, and 12% were still in school. Fine (1986) uses similar summary statistics to paint a bleak portrait of a New York City high school. After following 1,221 students who were ninth graders in fall, 1978, she found that only 20% ultimately graduated, 44% dropped out, 18% transferred to another school, 7% were "not found," 6% were discharged to military or business school, and 6% received a GED.

Despite their intuitive appeal, end-product statistics have at least two limitations: They are imprecise if there are many persisting students, and they fail to describe the distribution of risk over time. First, consider the problems arising from persisting students. Each year, more and more students, at all educational levels, are taking longer to complete their studies (Bowen, Lord, & Sosa, 1991; Fraser, 1989; Porter, 1990). How should persisters be categorized at the time chosen for end-product calculations? They are neither graduates nor dropouts. Because researchers handle this problem using so many different approaches, inconsistency remains the order of the day. In an attempt to be true to the information conveyed by these students, some place persisters in a separate category (e.g., Fraser, 1989; Iwai & Churchill, 1982; Mallette & Cabrera, 1991). Seeking simpler descriptions, others combine persisters with early graduates (e.g., Bryk & Thum, 1989; Panos & Astin, 1968), eliminate them from the calculations (e.g., Boli, Katchadourian, & Mahoney, 1988), or treat them in several different ways and compare the findings (Pascarella, Smart, & Ethington, 1986). Still others (e.g., Toles, Schultz, & Rice, 1986; Fine, 1986, described above) do not indicate how these students are treated. With survival methods, in contrast, persisting students pose no special problem—they simply have censored school careers.

Aware of these problems, many researchers handle persisting students through research design. They lengthen the data collection period so that the number of persisters decreases, hopefully until everyone firmly graduates or drops out (e.g., Gottfredson, 1982; Wright, 1964). To study university graduation patterns in the United Kingdom, for example, Johns and Taylor (1989, 1990) tracked students for 6 years arguing that "the number completing after six years is likely to be negligible" (1989, p. 221). Stroup and Robins (1972) went even further; they followed a cohort of boys born in St. Louis between 1930 and 1934 until the boys were men aged 30 to 36! Lengthening the data collection period is a good idea, but, even so, researchers can never be sure that the extended time frame is long enough for definitive computation of end-product statistics. In a critical appraisal of Johns and Taylor's study (1989, 1990), for example, McPherson and Paterson (1990) argue that the 6-year follow-up may be too short for Scottish universities, "where many degree courses are at least one year longer than those in the rest of the UK" (p. 380). And in her review of the literature on college dropouts who reenter school to complete their degrees, Spanard (1990) observes that "given that nontraditional programs report that the average age of adult students hovers around 36 or 37 years, it would be necessary to conduct a longitudinal study of at least twenty years to begin to identify proportions of dropouts who do return" (p. 333).

This returns us to the second problem with end-product statistics, even those

calculated on samples of students tracked for long periods of time: They fail to identify when students are most likely to make a transition. With survival methods, in contrast, researchers can model when students drop out, thereby determining whether they have dropped out by each of all the possible prior points in time. A further advantage of the survival analysis approach is that researchers can study simultaneously all the possible transitions—dropout, graduation, transfer, and so on—by constructing hazards models for each of the distinct competing risks.

Survival methods have been used by some researchers, especially those studying students at educational levels where there are no hard and fast rules about how long it takes to graduate. At the doctoral level, Civian (1990), for example, used survival methods to study degree progress among students at the Harvard University Graduate School of Education while Zwick and Braun (1988) used them to study students at Northwestern University. And for years, researchers studying college student attrition have presented sample survivor functions by semester or year (e.g., Bynum & Thompson, 1983; Eckland, 1964; Gosman, Dandridge, Nettles, & Theony, 1983; Iffert, 1955, 1957; Newlon & Gaither, 1980; Summerskill, 1962).

But at the high-school level, where so much research energy is targeted and the need for better information so acute, survival methods have yet to be widely applied. One notable and interesting exception is the work of Sween (1989), who tracked the 1978, 1979, and 1980 cohorts of freshmen through the 62 public high schools in Chicago. Although unable to distinguish between 9th- and 10th-grade dropouts (because of a state law requiring school attendance until age 16), she describes the distribution of risk across three grades using two types of survival statistic: the cumulative percentage of students who have dropped out by 10th, 11th, and 12th grades (the additive inverse of the survivor function) and the percentage of all dropouts who quit in 10th, 11th, and 12th grades, respectively.

In Table 2, we reproduce her summary statistics for a subsample of nonselective segregated high schools, which contain the largest pool of students in Chicago's public high schools. The second column of Table 2 contains the percentage of all students who "survived" each grade and indicates the elevated levels of dropout in the system. By the end of 12th grade, nonselective segregated high schools in Chicago had lost almost half of their students. After reviewing these statistics, Sween identified when students are most likely to drop out by examining the percentage of all dropouts who left in each year of high school. Noting that this percentage is highest in 9th/10th grade, she concluded that the early high-school years are the period of greatest risk.

TABLE 2

When do students drop out from nonselective segregated public schools in Chicago?
A comparison of three different computational approaches

High-school grade	Percentage remaining in school (% surviving)	Percentage of total dropouts leaving each year	Percentage of each grade that drops out per year (hazard)
9-10	83.9	38.6	16.1
11	71.3	29.4	15.0
12	58.4	32.0	18.1

Note. Adapted from Sween, 1989, Figure 3.1 and Table 3.2.

In the last row of Table 2, we extend Sween's analysis by presenting the sample hazard probabilities for dropping out, by grade. These statistics estimate the probability of dropping out in each grade among students who remained in school until that grade. Examination of the variation in sample hazard probabilities across grades leads to a different conclusion about student behavior. Although the early high school years are indeed risky, they are not the riskiest: Among continuing students, the risk of dropping out peaks in 12th grade.

How can the same data lead to two strikingly different conclusions about risk? By calculating the sample percentage of all dropouts who left in each of the grades, column 3 does not modify the *risk set*, the pool of students eligible to drop out in any particular grade. By estimating a hazard probability, column 4 does modify the risk set—earlier dropouts are omitted because they are no longer eligible to drop out (having already done so). In survival analysis, the risk of dropping out among 11th graders is calculated using only those students who made it to 11th grade. If an equal number of students drops out from a shrinking pool (consisting of those eligible to drop out), the sample hazard probability captures the greater risk associated with the later grade. By 12th grade, these schools have lost so many students that the risk of dropping out among those students who have managed to remain is higher than at any prior time.

The apparent anomaly arises from differences in the definitions of risk reflected in the two summary statistics. Both sets of estimated probabilities are "correct;" they simply answer different questions. Both identify periods of high risk, but they refer to different groups of students. Column 3 answers the question: For a randomly selected high-school dropout, when is dropout most likely to occur? Column 4 answers the more general question: For a randomly selected currently enrolled high-school student, when is dropout most likely to occur?

Both answers have implications for policy. But we believe that the definition of risk provided by survival methods is preferable for research, for it assesses the risk of dropping out among those students eligible to do so. If few students drop out, the two analytic methods produce similar conclusions; if many students drop out, as they do in this example, the analytic method matters. Although examining the proportion of dropouts who leave in each grade characterizes the population of dropouts, it does not describe the risk of dropping out over time among students in school. And perhaps ironically, the analytic method makes the most difference in places of greatest risk—among students in those schools where the dropout problems are most severe.

Identifying Important Predictors of When Students Drop Out and Graduate

Few researchers have modeled the relationship between when students drop out (or graduate) and student, family, and school characteristics. Analytic difficulties may explain part of this dearth. Without access to survival methods, researchers exploring such questions have had to implement strategic fix-ups to circumvent the inevitable analytic problems. Arguing thoughtfully that the timing of dropout was critical for understanding college attrition, for example, Barger and Hall (1965) moved forward with their analyses by collapsing their sample of students into two groups: those who quit before the end of the 10th week of the first semester and those who quit thereafter.

Noting that dichotomization sacrifices considerable variability in the outcome, other researchers have retained variation by crediting students whose careers are

censored by the end of data collection with as much schooling as the students had completed by that point in time. In their 2-year study of the relationship between drug use and student persistence, Kahn and Kulick (1975), for example, credited all persisting students with 24 months of school, regardless of how long the students ultimately stayed (see, too, Hendel, 1985; Moline, 1987; Wilson, 1981; Wolfe, 1985).

Stroup and Robins (1972) used another approach. Their extensive longitudinal data set had no censored observations, enabling them to capture variation in the timing of dropout and graduation with a six-level ordinal scale, ranging from 1 = "no high school" and 2 = "dropped out during 1st year of high school" to 5 = "dropped out during 4th year of high school" and 6 = "graduated from high school by age 21." They linked variation in this measure with predictors, but they did not identify periods of elevated risk, nor did they link variation in risk with the predictors they studied.

These important studies are, unfortunately, the exceptions. We believe that disinterest does not explain why so few investigators explore the timing of student transitions. Too many prominent educational researchers identify the importance of timing in students' decision-making processes (e.g., Astin, 1975; Finn, 1989; Tinto, 1987). Rather, we believe that the problem has been a lack of a coherent methodology that would allow researchers to: (a) model longitudinal risk profiles as a function of multiple predictors and (b) incorporate both censored and uncensored cases simultaneously. A similar view is held by Rumberger (1987), who noted that previous research on high-school dropouts has primarily looked for correlations between dropping out and a host of antecedents. He called for more multiwave studies investigating the causes of student dropout behavior and looking beyond family background characteristics to the students and their schools: "New research efforts should focus on developing multivariate, longitudinal, and comprehensive models of the causes and consequences of dropping out" (p. 119).

Shifts in methodology come slowly. Although current research is multivariate and comprehensive, it is not yet truly longitudinal. Researchers model the effects of multiple predictors, but they continue to ask only whether students drop out or graduate by a particular point in time. Some focus on student attributes (e.g., Ekstrom, Goertz, Pollack, & Rock, 1986; Rumberger, Ghatak, Poulos, Ritter, & Dornbusch, 1990); others emphasize school-related factors (e.g., Bryk & Thum, 1989; Stern, Dayton, Paik, & Weisberg, 1989; Wehlage & Rutter, 1986). And, whereas some researchers consider multiple termination points, they usually do so by conducting separate, but parallel, analyses. In some instances, they separately model dropping out and transferring (e.g., Bank, Slavings, & Biddle, 1990; Mallette & Cabrera, 1991), whereas in others they separately model the completion of specific grades (e.g., Butler, 1990) or the completion of specific academic milestones (e.g., Duker & Gaither, 1984; Girves & Wemmerus, 1988).

Only a handful of researchers has used the truly longitudinal models available under survival analysis. At the doctoral level, Civian (1990) and Zwick and Braun (1988) used hazard models to show how the risk of graduation differs by a student's department affiliation, demographics, ability, and financial aid package. At the high-school level, Mensch and Kandel (1988) used them to show that students who use drugs are more likely to drop out, whereas Barro and Kobstad (1987) used them to show that racial disparities in the risk of dropping out disappear after controlling statistically for student background characteristics.

But with these notable exceptions, educational researchers have yet to exploit the many advantages offered by survival methods. And although highly creditable, even these survival analyses have been constrained by restrictive, and potentially untenable, assumptions. In their path-breaking analysis of the 1982 follow-up to High School and Beyond, for example, Barro and Kolstad (1987) made the simplifying assumption that the hazard function was constant during the high-school years. But as Mensch and Kandel (1988) note (and as we have illustrated in Table 2), this assumption may be untenable because the risk of dropping out is likely to differ across high-school grades. Civian (1990) made a different restrictive assumption—that the proportional hazards assumption was met.

These shortcomings should not negate the important contributions of these pioneering studies. The researchers made simplifying assumptions because of analytic or computing difficulties beyond their control. Indeed, we hope that these studies are but the first of a new wave of research on students' careers, a wave characterized by the widespread application of survival methods. Much can be learned from even exploratory analyses of sample survival and hazard functions. Statistical modeling of the hazard profile will enable researchers to examine the effects of predictors that have previously been beyond their analytic reach, particularly those predictors that vary naturally over time. And through the application of competing risks survival analysis, researchers can model simultaneously the many paths that students take through school. We now briefly sketch two specific directions for future research that we believe are especially promising.

Promising types of predictors. As we discussed in the section on teachers' careers, hazard models can simultaneously incorporate time-invariant and time-varying predictors. We believe that the ability to examine the latter predictors, in particular, provides researchers studying students' careers with a new and unique analytic opportunity. Previous researchers have had little choice but to focus on time-invariant predictors—student and family demographics, school type, community characteristics, and the like. Whereas some have used the value of a time-varying predictor at a single instant (e.g., Barro & Kolstad, 1987, examined the effects of student academic performance in 10th grade on the risk of dropping out), to our knowledge, only Mensch and Kandel (1988) have actually linked a time-varying predictor (in their case, drug use) to the risk of dropping out.

Much more remains to be done. In a recent review of the research on college student attrition, Tinto (1988) writes:

Though it has long been recognized that the process of student departure is longitudinal, researchers have in fact done very little to explore the temporal dimensions of that process. Despite the continuing theoretical debate over the dynamics of student departure and the growing body of research on its character, there has been with a few notable exceptions virtually no discussion of the possible variation in that process. . . . Rather than pursue that possibility, past research has implicitly assumed that the process of student departure is essentially invariant over the course of the student career. (p. 438)

When reviewing the research on high-school withdrawal behavior, Finn (1989) made a similar point, arguing that it is time for researchers to view a student's decision to drop out as the culmination of a developmental process that begins in very early grades.

It is clear that to understand why students make the choices they do we must track them over time, noting carefully what is happening to them, how they are performing, and how they respond. What were a student's grades the semester before drop out? Was this a change from the previous semester? Did his or her family situation change? While the decision to drop out may be impulsive for some, for most it evolves gradually over time (Natriello, Pallas, & McDill, 1986; Pantages & Creedon, 1978). This is the advantage of survival methods. Time-varying predictors can capture potentially important changes in a student's life over time; hazard models can then relate these changes to the timing of educational transitions.

What do hazard models actually offer educational researchers studying student careers? Consider research on college persistence. In her meta-analysis of the effects of financial aid on persistence, for example, Murdock (1987) suggests that the effects of aid are strongest during students' later years in school. By incorporating into hazard models a student's financial aid award, course grades, and, if possible, measures of academic and social integration, a researcher could examine the effects of each of these inherently time-varying characteristics. Later examination of interactions between these time-varying characteristics and time (as described in detail in the teachers' careers section of this article) would permit a test of Murdock's hypothesis that the effect of financial aid is stronger later in students' careers. (For related but somewhat different approaches to the same research question, see the excellent studies by Stampen & Cabrera, 1988; Olsen & Farkas, 1989.)

The predictors included in hazard models are not limited to naturally occurring characteristics of students and their schools—they can also represent participation in experimental programs. At the secondary school level, one particularly important time-varying predictor that has yet to be studied within a survival analysis framework is participation in a dropout prevention program (Wehlage, Rutter, Smith, Lesko, & Fernandez, 1989). We emphasize it here because researchers evaluating the efficacy of interventions typically ask only if the program reduced the number of dropouts (e.g., GAO, 1986; Hahn, Danzberger, & Lefkowitz, 1987; Hamilton, 1986). Survival methods would allow researchers to determine whether (time-varying) participation in a dropout prevention program reduces (the year-by-year profile of) dropout risks. Other information describing a student's status prior to intervention can also be included in these models at the same time. But by including "treatment" as a predictor, researchers can answer questions about whether program participation reduced the risk of dropping out and whether the effect was greater (or smaller) for certain groups of students.

Modeling competing modes of exit from school. Although we can summarize the decisions of a cohort of students using sample survival and hazard functions and we can build hazard models that relate the risk of leaving school to student and school attributes, the many modes of exit from school complicate this process. A particularly compelling advantage of survival methods is that they allow us to model all modes of exit simultaneously as a set of competing risks.

The need to build models of competing risks is clear. Different students leave school in different ways for different reasons (e.g., see Morrow, 1986; Pantages & Creedon, 1978; Simpson, Baker, & Mellinger, 1980). In any cohort of high-school freshmen, for example, while many will graduate in 4 years, some will drop out before this time, others will be left back, and still others will graduate later, perhaps with a GED. There is no way to know in advance who will make which decision when.

Each student must be followed as long as possible so that we know when they finish or quit. Students can graduate, transfer, be expelled, drop out, or simply take longer to complete their degrees. The target event is always exit from school; the difference is how that exit is made. After deciding which modes of exit will be distinguished, the researcher models these events as competing risks.

We illustrate these ideas here by combining several modes of exit into a single pair of competing risks—graduation versus dropping out. If more modes can be distinguished reliably, they can also be modeled. Because these two risks compete to end each student's career, we conduct two simultaneous analyses, one for each mode of exit, describing the risk of that event—graduation or drop out. Both analyses include all students, but censoring is defined differently depending upon the event being studied. When modeling graduation, students who dropped out are censored at the time of dropout, while students who have neither dropped out nor graduated by the end of data collection are also censored, but at the end of data collection. When modeling dropout, students who graduated are censored at graduation, while students who have neither dropped out nor graduated by the end of data collection are also censored, but at the end of data collection. After identifying predictors of the two competing risks—graduation and dropping out—we can assemble a combined profile of the risk of leaving school over time that incorporates information about those factors associated with graduation and those factors associated with dropping out.

The strengths of this formulation are highlighted in Mensch and Kandell's (1988) excellent analysis of follow-up data collected as part of the National Longitudinal Survey of Youth. Using discrete-time hazard models, the authors explore the role of illicit drug use in predicting who drops out, graduates, or earns a GED. After controlling for factors known to be linked to dropping out (academic performance, socioeconomic status, and family structure), the authors find that

prior use of cigarettes, marijuana, and other illicit drugs increases the propensity to drop out and that the earlier the initiation into drugs, the greater the probability of premature school leaving. (p. 95)

They go on to find that "the usage of marijuana and other illicit drugs does not determine who among the dropouts acquires an equivalency certificate" (p. 112). The same predictor—illicit drug use—has a different effect depending upon the "event" being modeled. By using a competing risks formulation, researchers studying student careers can develop a more refined understanding of which factors affect which modes of exit.

Discussion

In an article entitled, "The High School Dropout Puzzle," Chester Finn (1987), then Assistant Secretary of Education wrote, "We don't all follow the same paths to similar destinations, nor do we all proceed at the same pace" (p. 8). This is a lesson that we should all bear in mind when studying teachers' and students' careers.

How can we best learn whether, and if so, when, people reach their educational destinations? How can we best learn why some people arrive sooner, while others take much longer? Over the years, empirical researchers have assembled a haphazard toolkit for answering questions like these. The approaches included rudimentary descriptive summaries and *ad hoc* statistical analyses—some informative, some potentially misleading. In hindsight, we can see that the best traditional approaches

fall naturally within the unified survival analysis framework. But the full complement of survival methods provides a much more powerful set of tools for answering a variety of questions about the "whether" and "when" of educational careers.

Survival methods offer many advantages over traditional approaches. They provide the longitudinal perspective necessary to model the complex paths that students and teachers take through schools. They can reflect dynamic and changing decision-making reality far better than static end-product models that emphasize the occurrence of single transition at a particular point in time. No longer must persisting individuals—those who have yet to quit or those who have yet to leave school—be treated in an *ad hoc* fashion; they can be included for as long as there are data to describe their behavior. And hazard models that describe the risks of termination can include information about many predictors simultaneously.

Of all the survival methods available, we believe that discrete-time survival analysis offers the most promise for exploring educational transitions. The application is natural; educational data are typically collected at regular intervals, not in continuous time. Discrete-time survival analysis does not require dedicated software; it can be implemented using routines available in most standard statistical packages. In addition, it facilitates investigation of the effects of time-varying predictors; it can be used to detect interactions between predictors and time (as when the effects of a predictor fluctuate with the passage of time), and it can be used to study the many competing risks of exit—voluntary and involuntary terminations among teachers and dropping out and graduation among students.

Survival methods are not new to educational research; they have been used successfully in other areas of inquiry, as when studying topics as diverse as the attainment of tenure (Mueller, 1986), the length of academic appointments in universities (Rosenfeld & Jones, 1987), the length of day care arrangements (Singer et al., 1980), and the length of time that children pay attention to lessons in elementary school reading groups (Felmlee & Eder, 1983). We believe that there are many more natural applications of these methods yet to be identified, for they are well suited for answering any research question about time. Researchers studying learning, for example, could use them to explore how long it takes students to master a skill or to move on to a higher stage of learning. So, too, could researchers use them to study student absenteeism and its causes (e.g., see Fitchman, 1988, 1989; Harrison & Hulin, 1989). In a companion article (Singer & Willett, 1991), we outline a wide variety of other potential areas of applications in education and psychology and discuss many issues that arise when designing studies that will ultimately use survival methods.

We encourage educational researchers considering asking "Whether?" to think about whether they would really like to know "When?". We believe that many researchers interested in the timing of educational transitions have reframed their research questions because they did not know how to fully exploit the data they had gathered or because they were unsure how to incorporate both censored and noncensored observations in their analyses. Survival methods provide straightforward, easily applicable tools for appropriately analyzing the timing of educational transitions. We urge researchers to learn about them so that, when they encounter such questions, they will collect and analyze multiwave data appropriately, ensuring that their conclusions will withstand stringent analytic scrutiny.

Notes

¹ Although the sample of teachers used in Figure 1 contains teachers hired in each of the years 1972-1978, all teachers were tracked from a common career point: entry into teaching.

² When time is measured continuously, a logarithmic transformation is used for the same reason.

³ For pedagogic reasons, we have taken mathematical liberties with the phrase *proportional hazards*. The notion of *proportional hazards* actually arises in the context of continuous-time hazard models in which *log-hazard*, rather than *logit-hazard*, is modeled as a linear function of predictors (see Anderson, Auquier, Hauck, Oakes, Vandaele, & Weisberg, 1980, Appendix IIIA). In continuous-time models, differences in the elevation of the log-hazard profiles correspond exactly to magnifications and diminutions in the raw hazard profile. Hence, the untransformed hazard profiles are indeed proportional, as stated. In discrete-time models, however, the proportionality of the raw hazard profiles is only approximate because vertical shifts in logit-hazard correspond to magnifications and diminutions of the untransformed hazard profile only when the magnitude of the hazard probability is small (say, less than .15 or .20). In empirical research, discrete-time hazard is usually of about this magnitude, or less, and therefore the approximation tends to hold quite well in practice. This distinction is discussed in greater detail in Singer and Willett (in press).

⁴ The comments in the text refer to SAS Version 6.06.01 as implemented under VMS on a MicroVax computer. SAS Institute has recently announced the forthcoming PROC PHREG that will carry out "Cox Regression With Time-Dependent Covariates" (*Arnstarr News*, 1991).

APPENDIX

Sources of technical information on survival analysis

In the body of this article, we have purposefully avoided the discussion of technical statistical issues that arise in survival analysis; indeed, we have gone to great pains to ensure that the text is relatively free of technicality. Our goal has been to make a strong case for the use of survival methods in educational research and to illustrate how these methods build directly on, and largely subsume, other approaches used in the study of teacher and student careers. For readers considering using survival methods in their research, this appendix provides references to other written materials that they might want to consult before embarking on a study.

Readers interested in acquiring a more sophisticated background in these methods can choose among a wide range of published material, both in books and in scholarly journals. Allison's (1984) introductory monograph provides an excellent starting point for readers familiar with regression. It provides a well-documented, accessible, and largely nontechnical introduction to a broad range of survival methods. In less than a hundred pages, Allison touches on most of the important issues facing the user of survival analysis, including: discrete- versus continuous-time methods, the proportional hazards model and partial likelihood estimation (Cox regression), and the analysis of competing risks and repeated events. A more expanded presentation at a similar level is given by Blossfeld, Hamerle, and Mayer (1989).

Scattered throughout the scholarly literature is a variety of accessible articles that can be used to supplement Allison's (1984) overview. Many of these provide nontechnical reviews of the application of survival methods in particular, substantive areas. Singer and Willett (1991) provide a nontechnical discussion of applications of survival analysis in psychological and educational research, focusing specifically on issues of research design and data analysis. Anderson et al. (1980) use a medical setting to present a readable introduction to many aspects of survival analysis, ranging from displays and single-number summaries through life-table testing and hazards modeling. Kiefer (1988) surveys the application of survival analysis to economic duration data, paying particular attention to the effects of using different parametric functions to represent the hazard function, the assumptions underlying the hazards models, estimation of the parameters, and the checking of model specification.

Readers wishing to supplement these introductions with greater technical detail should consult one of the several, standard texts. Although mathematically complex, Kalbfleisch and Prentice (1980) is a thorough and well-written source. Other texts of similar stature are Cox and Oakes (1984) and Miller (1981). In addition, there has been important methodological work on survival methods (known in sociology as event history methods) pioneered by Tuma (1982) and her colleagues (Mayer & Tuma, 1990; Tuma & Hannan, 1984) and others (Peterson, 1991). In recent years, most mainframe computer packages have implemented some kind of survival analysis software. As of summer, 1991, BMDP (Dixon, 1990) contained the most comprehensive survival analysis subprograms: 1L can be used to examine life tables and estimate sample survivor functions and is able to compare them across groups, and 2L permits the fitting of hazard models with both time-invariant and time-varying covariates. Two procedures in SAS (SAS Institute, 1990) have similar purposes: LIFETEST can be used for the estimation and comparison of sample survivor and hazard functions, and LIFEREG is able to fit a variety of semiparametric and parametric hazard models, although there is currently no facility for including time-varying predictors in the models.⁴ Finally, SPSS (SPSS[®], 1986) contains a subprogram, SURVTVAL, that estimates and compares sample survivor and hazard functions but cannot currently fit models of hazard as a function of predictors.

In contrast to mainframe statistical packages, which seem to have been somewhat slow in implementing survival routines, dedicated software designed for the personal computer has mushroomed. In 1984, when his review of the field was first printed, Allison made no specific reference to PC-based software in his Appendix C on "Computer Programs" (Allison, 1984); in 1989, in a thorough survey of the availability of PC-based survival analysis software, Goldstein and his colleagues reviewed 14 sophisticated survival analysis packages available for MS/PC-

(continued on p. 442)

APPENDIX (Continued)

DOS computers alone (Goldstein et al., 1989). For readers who will conduct their analyses on a personal computer, this article compared the attributes and requirements of each of the 14 different pieces of software (see also Harrell & Goldstein, 1992).

We have argued that educational career data are often collected in discrete-time, rather than continuous-time. When this is the case, discrete-time survival analysis provides a straightforward and accessible approach to data analysis (Allison, 1982; see also Efron, 1988; Laird & Olivier, 1981). Discrete-time hazard models not only allow the testing and, if necessary, the relaxation of the proportional hazards assumption but also have other advantages—they are easy to apply; they facilitate the recapturing of the baseline hazard and survivor functions, and they can be estimated with standard logistic regression software. Although a discussion of techniques for estimating the parameters of a discrete-time hazard model is also beyond the scope of this article, we provide a detailed discussion of these issues (including SAS computer code) in three companion articles (Singer & Willett, 1991, in press; Willett & Singer, 1991).

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