form of an additive DISTURBANCE (or error) TERM. Let the (unobserved) individual variation be represented by u_i:

$$E(y_i|X_i) = \exp(X_i b + u_i) = e^{X_i b + u_i}$$
$$= e^{\sum_j b_j x_{ji} + u_i} = e^{\sum_j b_j x_{ji}} \times e^{u_i}.$$

If the variance of u_i happens to be 0, then this degenerates to a Poisson model (because $e^0 = 1$). However, if we posit that u_i has a GAMMA distribution, then the observed distribution of y_i would be the negative binomial. It is typical to assume that $E(u_i) = 0$, so that "on average" the heterogeneity observed among cases has no effect. That is to say, the expected value of a Poisson or negative binomial model is the same. However, when the variance of $u_i > 0$, the dispersion of the negative binomial distribution is greater. Long's (1997) textbook offers an excellent treatment of this issue.

Many extensions of the count model framework are available or are being pioneered in the advanced literature of statistics. The approach can be extended to situations in which one observes a greater than expected number of zeroes in the counts. An encyclopedic treatment of count models was presented by Cameron and Trivedi (1998).

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EVENT HISTORY ANALYSIS

Event history analysis is a technique that allows researchers to address not only whether an event occurs but also when it occurs. An event is a change from one state to another, and the dependent variable is the time until the event occurs. Event history analysis is ideally suited to the study of longitudinal change and can be thought of as extending LOGIT/PROBIT ANALYSIS and EVENT COUNT MODELS to take into consideration the timing of the event(s).

Two common complications arise in longitudinal data analysis that motivate the use of event history analysis. First, censored observations exist in the data when information about the duration (the amount of time an observation spends in a particular state) is incomplete. This may occur, for example, because the observation did not experience the event of interest prior to the end of the study or because the observation is lost in follow-up, perhaps because the subject moved and could not be located. Second, time-varying covariates (or independent variables) have values that change over time. For example, in a study of the timing of challenger entry in a congressional election, the amount of money raised by an incumbent legislator could be a time-varying explanatory variable across the election cycle. Event history techniques can readily incorporate censored observations and time-varying explanatory variables. The inclusion of time-varying covariates in event history analysis can lead to novel information regarding how the risk of an event occurrence changes in relation to changes in the value of that covariate.

HISTORICAL DEVELOPMENT

Event history analysis is also referred to as *duration*, *survival*, or *reliability analysis*, depending on the substantive origins of the discussion (medicine and engineering for the latter two terms, respectively). Early applications involved life table analysis by Kaplan and Meier (1958), but the historical roots can be traced back even further to the late 1600s (Hald, 1990). There was an increased use of the technique during World War II because of concerns over the expected reliability of military equipment. The path-breaking work of D. R. Cox (1972) is credited with another period of expansion in the use of event history analysis as a result of his development of semiparametric techniques. His work is likely to be heralded as one of the top statistical achievements in the 20th century. Applications in medicine and the social sciences have increased greatly as a result of the less restrictive semiparametric Cox regression model and its various extensions, which are built upon the mathematics of counting processes (Therneau & Grambsch, 2000).

PARAMETRIC AND SEMIPARAMETRIC MODELS

Both parametric and semiparametric models are available in event history analysis. Analysts studying mechanical systems typically use parametric models, which assume that the time until the event of interest follows a specific distribution, such as the exponential. Studies of human behavior and biology typically use the less restrictive semiparametric Cox model, which leaves the particular distributional form of the duration times unspecified. Blossfeld and Rohwer (2002, pp. 180, 263) argued that social science theory rarely provides the justification for a specific parametric distribution and instead advocated for use of the Cox model.

A key concept in the estimation and interpretation of an event history model is the HAZARD RATE. The hazard rate gives the rate at which observations fail (or durations end) by time t given that the observation has survived through time $t - 1$. In other words, it can be interpreted as the probability that an event will occur for a particular observation at a particular time. The risk set refers to those observations that are still "at risk" of experiencing the event of interest. Once the observation experiences the event at time t, the observation exits the risk set and is no longer part of the data set being analyzed at $t + 1$. The hazard rate has substantive appeal in that the event of interest is conditional on its history. For example, given that a war has lasted t periods, what is the likelihood that it will end in the subsequent period? The hazard rate for the Cox model may be written as

$$h(t|X_i) = h_0(t)e^{X_i\beta},$$

where $h_0(t)$ is an (unspecified) baseline hazard function and X_i are covariates for observation i.

MODEL ASSUMPTIONS AND MODEL FITTING

The major assumption to be checked when fitting event history models is the proportional hazards assumption. Most event history models, including the Cox model, assume that the hazard functions of any two individuals with different values on one or more covariates differ only by a factor of proportionality. Put differently, the baseline hazard rate varies with time but not across individuals, so that the ratio of the hazards for individuals i and j are independent of t and are constant for all t:

$$\frac{h_i(t)}{h_j(t)} = e^{\beta(X_j - X_i)}.$$

Estimation of Cox's model when hazards do not satisfy the proportionality assumption can result in BIASED and inefficient estimates of *all* parameters, not simply those for the covariate(s) in question. The proportional hazards assumption should be checked with Harrell's ρ for individual covariates and with Grambsch and Therneau's global test for nonproportionality (Box-Steffensmeier & Zorn, 2001; Therneau & Grambsch, 2000). If evidence of nonproportionality is found (and, in most social science research, proportionality is more the exception than the rule), then the potentially nonproportional covariates should be interacted with ln(time) or other appropriate transformations of time. Such interactions allow each interacted covariate's effect on the hazard of conflict to vary monotonically with the duration of the event being studied. Relaxing this assumption allows scholars to test whether the effects of covariates change over time and permits a more nuanced understanding of the phenomenon being studied. Moreover, nonproportionality tests, and the residuals upon which they are based, are increasingly easy to obtain in commonly used software packages for analyzing duration data.

If parametric models are estimated, the assumption of the chosen parametric distribution needs to be tested, and the proportional hazard assumption may still need to be assessed (for example, the Weibull model also assumes proportional hazards). The generalized gamma distribution is an encompassing model for several commonly used parametric distributions and thus may serve to help adjudicate among competing nested models. Because the parametric models are estimated by maximum likelihood and the properties of these estimators are well known, the standard battery of goodness-of-fit indices and statistics are directly applicable to the parametric modeling framework, for example, use of the LIKELIHOOD RATIO test or the Akaike information criterion (AIC). However, the principal advantage of the Cox model is not having to make assumptions about the nature and shape of the baseline hazard rate, and thus the Cox model should be the first choice among modeling strategies for social scientists (Box-Steffensmeier & Jones, 1997).

Another underlying assumption of almost all event history models is that all observations eventually will experience the event of interest. This assumption can be relaxed by estimating a split-population model. (These models are also known as cure models in biostatistics, a name based on the idea that part of the population is cured.) As examples, in studies of the timing of campaign contributions, split-population models do not assume that every political action committee (PAC) eventually will give to every political candidate, and in studies of criminal recidivism, the models do not assume that all former prisoners eventually will return to prison. Split-population models estimate the proportion of observations that will not experience the event, together with the parameters characterizing the hazard rate for the proportion experiencing the event. These models allow differential effects for the covariates on whether the event occurred and its timing. For example, a covariate may have a positive effect on whether a contribution is made but a negative effect on when it is made. The appeal of the log-likelihood in a split-population model is that observations that never experience the event contribute information only to part of the function. As such, the log-likelihood "splits" the two populations (Schmidt & Witte, 1988).

DIAGNOSTICS

As in the traditional regression setting, residual analysis in the event history analysis context is a method of checking specification or model adequacy. Various pseudo-residuals are defined in event history analysis for checking different aspects of a model, taking into account the complication that censoring adds to the definition of a residual. In addition to their use in testing the proportional hazards assumption, pseudo-residuals can help the researcher in assessing the model fit, functional form of the covariates, and influence of particular observations. For example, the martingale residuals can be calculated to test whether a given covariate X should be entered linearly, as a quadratic, or in one of the many other possibilities. These diagnostic methods should be used routinely in applications to ensure the integrity of the model (Therneau & Grambsch, 2000).

SINGLE AND MULTIPLE EVENTS

In addition to studying a single-event occurrence, where once the event is experienced, the observation leaves the risk set, event history analysis also can consider multiple events. Event history models for multiple events take into account the lack of independence across events, because ignoring the correlation can yield misleading variance estimates and possibly biased estimates of the coefficients.

Multiple events can be simultaneous unordered events whose risk of occurring varies. In this case, we consider one of several types of "failure," and such processes are referred to as *competing risks.* For example, a member of the U.S. House of Representatives may leave the House in a variety of substantively interesting ways that we should recognize and incorporate into our models, such as being defeated in the primary, being defeated in the general election, running for higher office, or retiring. We would expect that the hazard rate and effects of the covariates will differ across these types of departure.

One can also consider ordered multiple (or *repeated*) events. Repeated-events processes, in which subjects experience the same type of events more than once, are common in fields as diverse as public health, criminology, labor and industrial economics, demography, and political science. Failing to account for repeated events implicitly assumes that the first, second, third, and subsequent events are statistically independent of one another, a strong and usually untenable assumption. The conditional interevent (or gap) time model will be applicable for most instances of repeated events in social science. However, the nature of the means by which repeated events occur (that is, sequentially or simultaneously) and the corresponding construction of the "risk set" for each observation should provide the primary motivation for selecting one model over another (Box-Steffensmeier & Zorn, 2002).

EXAMPLE AND INTERPRETATION

Many applications of event history analysis exist in the social sciences, and the substantive realm of problems being studied is greatly expanding. Examples include studies of the duration of unemployment, peace, survey response time, criminal recidivism, marriages, public policy program implementation, and lobbying. Table 1 presents typical Cox proportional hazard estimates, using militarized conflict data. (Efron's approximation for ties is used in the estimation of the Cox model. The Breslow approximation was the first approximation developed and is not generally

Table 1 Cox Proportional Hazards Model of Conflict

	β (S.E.)	*p value*
Democracy	−0.439(0.100)	< 0.001
Growth	−3.227(1.229)	0.009
Alliance	−0.414(0.111)	< 0.001
Contiguous	1.213(0.121)	< 0.001
Capability ratio	−0.214(0.051)	< 0.001
Trade	−13.162(10.327)	0.202
Wald or LR test	272.35 (*df* = 6)	< 0.001

NOTE: $N = 20{,}448$.

recommended, whereas the exact likelihood option typically gives results extremely similar to those obtained with the Efron approximation while taking considerably longer to converge.)

Oneal and Russett's (1997) widely used data on the relationship among economic interdependence, democracy, and peace is used for the illustration. The data consist of 20,448 observations on 827 dyads (i.e., pairs of states such as the United States and Canada), between 1950 and 1985. We model the hazard of a militarized international conflict as a function of six primary covariates (some of which vary over time): a score for *democracy* (a dyadic score for the two countries which ranges from −1 to 1), the level of *economic growth* (the lesser rate of economic growth, as a percentage, of the two countries), the presence of an *alliance* in the dyad (a dummy variable indicating whether the two countries were allied), the two nations' *contiguity* (a dummy variable for geographic contiguity), their military *capability ratio* (a ratio measuring the dyadic balance of power), and the extent of bilateral *trade* in the dyad (a measure of the importance of dyadic trade to the less trade-oriented country; it is the ratio of dyadic trade to the gross domestic product of each country). (See Oneal and Russett, 1997, for details of the variables and coding.)

Liberal theory suggests that all variables except contiguity ought to decrease the hazard of a dispute, while contiguity should increase it. The likelihood ratio (LR) test at the bottom of Table 1 shows that the specified model is preferred to the null model (i.e., the null hypothesis is that there is no statistically significant difference between the specified model and the null model of no independent variables). All the coefficients are in the expected directions, and all except that for trade are statistically significant. Note that the Cox model does not have an intercept term; it is absorbed into the baseline hazard. Because the coefficients of the Cox model are parameterized in terms of the hazard rate, a positive coefficient indicates that the hazard is increasing, or "rising," with changes in the covariate (and hence survival time is decreasing), and a negative sign indicates the hazard is decreasing as a function of the covariate. For this model, the negative coefficient of –0.439 for democracy suggests that dyadic democracy reduces the likelihood of conflict; that is, dyadic democracy results in a lower hazard (and longer survival time). Box-Steffensmeier and Jones (1997) used the percentage change in the risk of experiencing the event to understand the impact of the effect (p. 1434). For a dichotomous independent variable, the percentage change in the risk of experiencing the event is

$$100[e^{(\beta_k \times 1)} - e^{(\beta_k \times 0)}]/e^{(\beta_k \times 0)}.$$

Negative coefficients produce values of $e^{(\beta_k \times 1)}$ that are less than one, and therefore produce negative percentage changes. The interpretation for a continuous independent variable is similar:

$$100[e^{[\beta_k \times (x+\delta)]} - e^{(\beta_k \times x)}]/e^{(\beta_k \times x)}.$$

This gives the percentage change in the hazard rate for a δ-unit change in the independent variable, x. So, a one-unit increase in the democracy variable corresponds to a $[(e^{(-0.439)} - 1) \times 100] = 36\%$ decrease in the hazard of conflict at any given time.

In actuality, the militarized conflict data are characterized by large numbers of repeated events; for example, Britain and Germany fought each other in both World War I and World War II. Box-Steffensmeier and Zorn (2002) used these data to illustrate repeated events duration modeling and show that important differences are uncovered by taking into account the dependence generated from repeated conflicts.

Social science theories are increasingly focused on change processes, and temporal data are becoming widely available. Event history analysis is ideally suited for leveraging these research elements. The flexibility of the techniques, recent extensions for multiple events, and the incorporation of the observation's history about the events of interest are all compelling reasons to expect the use and popularity of event history techniques to increase in the social sciences.

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EVENT SAMPLING

Event sampling refers to a diverse class of specific empirical methods for studying individual experiences and social processes within their natural, spontaneous context. Event sampling procedures are designed to obtain reasonably detailed accounts of thoughts, feelings, and behaviors as they occur in everyday life. Examples include the experience sampling method (ESM), in which respondents are signaled at random moments during the day and asked to describe their activity at that exact moment, and daily diaries, in which at the end of each day, for some period (typically ranging from 1 week to 1 month), respondents report their experiences on that day. In one typical ESM study, 50 college students were signaled by pagers seven times per day for 1 week. When signaled, students with higher need for intimacy (as assessed on a projective personality test) were more likely to be thinking about people and relationships, were more often engaged in conversations with others and less likely to wish to be alone, and reported more positive affect if they were socializing (McAdams & Constantian, 1983).

Event sampling methods require that participants monitor and describe their ongoing activity along dimensions and according to schedules and formats defined by the researcher. Event sampling has three fundamental rationales that differentiate it from other common research paradigms (e.g., laboratory experiments, surveys): (a) that because behavior is influenced by context, it is important to sample behavior in its natural environment; (b) that global, retrospective reports are often biased by people's limited abilities to remember and summarize numerous events over time; and (c) that accounts of seemingly ordinary, everyday experience, when properly examined, are capable of providing valuable insights about human behavior. Topics for which event sampling methods have been employed profitably include emotion, social interaction, pain, smoking, stress and coping, student motivation, exercise, eating disorders, psychopathology, self-relevant cognition, personality, intergroup relations, and evaluations of drug treatments and therapeutic interventions.

Most event sampling studies employ one of three general protocols: *time-contingent responding*, in which participants report their experiences at fixed intervals (e.g., daily, hourly); *event-contingent responding*, in which a report is solicited whenever a predefined event occurs (e.g., smoking a cigarette, conversing with a friend), and *signal-contingent responding*, in which participants describe their experiences when signaled to do so by some device (e.g., a pager or a preprogrammed portable computer). Signals may follow a fixed or random schedule. Although event sampling was originated with simple paper-and-pencil responses, recent developments in electronic recording devices [e.g., personal digital assistants (PDAs) and voice recorders], as well as in ambulatory physiological monitoring, have added considerably to the validity, flexibility, and range of these methods.

Event sampling is not limited to participant self-reports. For example, in an observational study of schoolchildren, observers might code the behavior of a target child (e.g., what the child is doing, with whom he or she is currently interacting, visible affective expressions, and so on) according to any of the above schedules (e.g., every 10 minutes, after conflict, or following a randomized schedule, respectively).

In a typical event sampling study, a researcher might obtain a series of detailed descriptions of adolescents' momentary moods and actions across a 2-week period. These records could then be used in several ways: for