Event History Analysis

MULTIPLE KINDS OF EVENTS

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In the previous chapters all the events under study were treated as though they were exactly alike. Thus, in Chapter 2 we did not distinguish among different kinds of job changes, and in Chapter 3 all arrests were treated the same. Often this will not do. In some cases, lumping together different kinds of events may be completely inappropriate. Even when it is appropriate, however, a more refined analysis in which different kinds of events are examined separately is often desirable.

Fortunately, no new methodology is required. The methods already discussed for single kinds of events can also be used with multiple kinds of events; they just have to be applied in more complicated ways. Unfortunately, there is still much confusion surrounding this topic, and I believe that it is largely due to the fact that there are multiple kinds of "multiple kinds of events." This phrase really describes several quite different situations, each requiring a different approach to analysis.

A Classification of Multiple Kinds of Events

The first contribution of this chapter will be a classification of these different situations. For simplicity let us assume that there are only two kinds of events. Generalizations to more than two kinds of events should be apparent. (Usually, the number of different kinds of events will be a somewhat arbitrary choice of the analyst.) Also, we shall continue to assume that events are not repeated, leaving that complication for the next chapter.

The first major class may be described as follows:

I. The occurrence or nonoccurrence of an event is determined by one causal process; given that an event occurs, a second causal process determines which type occurs.

It is easy to think of examples that fall in this class. Consider the event of buying a car, and suppose we distinguish buying an American car**[p. 43 ↓]** from buying a foreign car. It is implausible that distinct causal processes lead to each of these two types of events. Rather, one first decides to buy a car; then, independent of that decision, one decides whether that car is to be an American or foreign car. It is likely that rather different explanatory variables affect each of these decisions. Another example is provided by the event of a visit to a physician, where we distinguish visits to osteopaths from visits to M.D.s. Again it is most plausible that the decision to visit some kind of physician is distinct from the decision of what kind to visit. It doesn't matter which precedes the other; the important ingredient here is that one decision is distinct from the other.

For this class of “multiple kinds of events,” the appropriate strategy for analysis is one that is isomorphic to the structure of the decisionmaking process. One first uses the event history methods described in the previous chapters to model the occurrence of the event, making no distinction between event types. Then, looking only at those individuals for whom events occurred, one uses an appropriate technique for modelling the causal process which determined the type of event. An obvious choice would be binomial logit analysis (or multinomial logit analysis if there are more than two types).

The second broad class of “multiple kinds of events” consists of those situations in which the following is true:

II. The occurrence of each event type has a different causal structure.

A different causal structure means either that different explanatory variables affect the occurrence of each event type, or that the same explanatory variables have different coefficients or different functional forms. Rather than providing examples of this general class, let us proceed immediately to the four subclasses. We shall also postpone discussing the method of analysis until all four subclasses have been described.

IIa. The occurrence of one event type removes the individual from risk of the other event type.

Often described as “competing risks,” this class has received much attention from biostatisticians and demographers. The classic example is death from competing causes. Clearly there are different causal processes leading to death from heart disease and death from cancer. Yet a person who dies of heart disease is no longer at risk of dying of cancer, and vice versa. There are also many examples in the social sciences. It is**[p. 44 ↓]** very likely, for instance, that voluntary job terminations occur as a result of different causal processes than involuntary job terminations, if only because different decision makers are involved in the two types of termination. Yet once a person quits a job, he or she is no longer at risk of being fired. And once fired, a person no longer has the option of quitting. A similar example is marital dissolution, where divorce is distinguished from death of a spouse.

IIb. The occurrence of one type of event removes the individual from observation of other event types.

In studies of human migration, one might distinguish moves within a country from moves between countries. It would not be uncommon for individuals to be lost to further study if they moved out of a country. Even though such an individual is no longer observed, he or she would still be at risk of a within-country move.

This example is a asymmetric in that individuals who move within a country are still at risk of a between-country move and may continue to be observed. It is easy to imagine symmetric cases, however. For example, a study of criminal recidivism may distinguish arrests for violent and nonviolent crimes. If the follow-up does not continue past the first arrest, then the study would fall into class IIb.

IIc. The occurrence on one kind of event affects neither the risk of occurrence nor the observation of other kinds of events.

While there are probably no two kinds of events that are absolutely unrelated, there are many cases that for all practical purposes, can be treated as if there were no relationship. Suppose, for example, that one event is voting in an election and the other is a divorce. Or perhaps one kind of event is getting a raise and the other kind is having a car accident.

IId. The occurrence of one kind of event raises or lowers (but not to zero) the hazard of the other kind of event.

It is easy to think of examples in this class. For unmarried women, getting pregnant increases the hazard of marriage. Marriage, in turn, increases the hazard of giving birth. Getting promoted reduces the hazard of quitting a job. Becoming employed reduces the hazard of being arrested.

Estimation for Multiple Kinds of Events

[p. 45 ↓] We now consider how to deal with these four subclasses. Class IIc is easy. If the occurrence of an event has no effect either on the observation or risk of occurrence of another event, then the first event can be completely ignored in studying the second event. Thus, this class is effectively the same as that discussed in the previous chapters.

On the other hand, if the occurrence of one event raises or lowers the hazard of the occurrence of the other event (class IId), then surely the first event must be taken into account in studying the second event. Again, however, we already have a method for doing this. The trick is to use the occurrence of the first kind of event to define a time-varying explanatory variable in the analysis of the second kind of event. Thus, in the biochemistry example, a time-varying dummy variable indicating a change in rank was used to predict the occurrence of an employer change. Similarly, in the analysis of arrests, a dummy variable was included to indicate whether or not the person was employed in each week. Alternatively, one could create a variable measuring the length of time since employment began. In fact, there is no reason why both variables could not be included as explanatory variables.

Class IIb is quite similar to what has already been described as censoring: An individual is removed from observation at some point prior to the occurrence of the event of interest. The difference here is that censoring is now an event in its own right. Despite this difference, the best available analytic strategy remains the same. Each event type is analyzed separately using the models and methods of the previous chapter. Events that remove the individual from observation are treated just as if the individual were censored at that point in time. For example, in analyzing the causes of within-country migration, individuals who made between-country moves (and hence could not be followed up) would be considered censored at the time of the between-country move.

Although I know of no better way to handle this situation, it is not entirely unproblematic. Recall that all the event history methods described so far require that censoring times be independent of event times. That requirement still stands even though censoring is now a distinct type of event. Thus, in the migration analysis just proposed, it must be assumed that times of between-country moves are independent of times of within-country moves, an assumption that may not be plausible. While it is possible to formulate and estimate models that build in some dependence, it is impossible to distinguish them empirically from models that specify independence.

[p. 46 ↓] Class IIa (competing risks), in which the occurrence of an event removes the individual from risk of other events, is the one most commonly discussed in the event history literature. Accordingly, it is the one to which we shall devote the most attention. It is superficially similar to class IIb, just considered, and indeed the basic message is the same. Methods for single kinds of events may be applied separately to each kind of event. In analyzing each event, the individual is treated as censored at the occurrence of any other kind of event. Because of the importance of this result, let us spend a little time on the background and the argument. Then we can proceed to an example.

Models for Competing Risks

There are several ways to approach the problem of competing risks, but the most common is to begin by defining what are known as “type-specific” (or “cause-specific”) hazard functions. Suppose there are m different kinds of events and let j = 1, …, m be the running index distinguishing the different kinds of event. Let $P_j(t, t + s)$ be the probability that event type j occurs in the interval between t and t + s, given that the individual is at risk at time t. Note that the individual is *not* at risk at time t if any of the m events have occurred prior to t.

The type-specific hazard rate is then defined as

$$h_j(t) = \lim_{s \to 0} P_j(t, t + s)/s \qquad [16]$$

Thus, each event type has its own hazard function. It can be shown that the overall hazard function h(t), which is the hazard for the occurrence of any of the m events, is just the sum of all the type-specific hazard functions.

For each of these type-specific hazard functions, one can develop a model for dependence on time and on the explanatory variables. Any of the models already discussed would be reasonable candidates. These models may be very much alike, or they can be completely different for each kind of event. In any case, it can be shown that the likelihood function (which is maximized in maximum likelihood estimation) for the data can be factored into a separate likelihood function for each kind of event. Moreover, those factors look exactly like likelihood functions for single kinds of events with all other events treated as censored. Thus maximum likelihood or partial likelihood estimation can be done**[p. 47 ↓]** separately for each event type, using the methods described in the previous chapters.

That does not mean that estimating separate models for each type of event is the only way to proceed. In fact the RATE program does simultaneous estimation for multiple kinds of events. The importance of this result is that, at a theoretical level, there is nothing really new about models for competing risks. And at a practical level, estimating models separately for each kind of event gives one much greater flexibility and control over the kinds of models estimated. For example, one could specify a Weibull regression model for one kind of event and a Gompertz regression model for another kind of event. Or more likely, the models for different kinds of events might have different explanatory variables or the same explanatory variables transformed in different ways. Most importantly, one can ignore event types that are of little or no interest. In a study of marital dissolution, for example, if one is only interested in the causes of divorce, it is not necessary to estimate models for both divorce and death of a spouse.

An Empirical Example of Competing Risks

For an example of a competing risks analysis, we again consider data from a study of criminal recidivism. Known as TARP (Rossi et al., 1980), the study was a large-scale replication of the experiment described and analyzed in Chapter 3. Approximately

4000 inmates released from prisons in Texas and Georgia were randomly assigned to experimental treatments involving various levels of financial aid and job search assistance. They were followed for one year after release, when a search was made of public records for any arrests which occurred during the follow-up year. For this example, the analysis is restricted to 955 Georgia convicts interviewed during the follow-up year. The event of interest is the first arrest to occur after release, so that those with no arrests during the one-year period are treated as censored.

Various types of arrests will be distinguished, depending on the type of crime allegedly committed. In one phase of the analysis, we shall distinguish crimes against property (robbery, burglary, larceny, and so on) from all others. In a later phase, we shall further subdivide nonproperty crimes into violent and nonviolent crimes.

Continuous-time methods are most appropriate since the exact day of each arrest is known. Using the SAS PHGLM procedure, we shall estimate proportional hazard models of the form

$$\log h_j(t) = a_j(t) + b_{j1}x_1 + b_{j2}x_2 + \ldots \qquad [17]$$

[p. 48 ↓] where the j subscripts indicate that there is a different set of coefficients and a different arbitrary function of time for each arrest type. Explanatory variables include education, marital status at time of release, age at release, age at earliest known arrest, sex, number of previous convictions for crimes against persons, number of previous convictions for crimes against property, a dummy variable indicating whether the incarceration was for a crime against persons, a dummy variable indicating whether the incarceration was for a property crime, and a dummy variable indicating whether or not the person was released on parole. Tha analysis is simplified by the fact that none of these is a time-varying explanatory variable.

We begin by estimating a model which does not distinguish different kinds of arrests. There were 340 persons with at least one arrest, so the remaining 615 persons with no arrests were censored at 365 days. The estimated coefficients are given in Table 4, column 1. Only four of the 11 explanatory variables are significant at the .05 level or beyond: age at initial arrest, number of previous property convictions, incarceration for a property offense, and release on parole. Note that the dummy variable for financial aid does not have a significant effect, and even has a sign opposite that which was expected. Thus it appears that financial aid is not effective in reducing recidivism.

This initial model is unsatisfactory, however, because theory suggests that financial aid should reduce property offenses but not other offenses. It is also possible that other variables may have different effects on different kinds of arrests. To examine this possibility, we subdivide arrests into 192 property arrests and 148 nonproperty arrests, and then estimate a separate proportional hazards model for each type of arrest. When estimating the model for property arrests, persons whose first arrest was for a nonproperty arrest are treated as censored at the time of that arrest. Similarly, in the model for nonproperty arrests, property arrests are equivalent to censoring.

This may seem like an artificial example of competing risks since, after the first arrest, the subjects continued to be observed and at risk of both kinds of events. It could, in fact, be reasonably argued that the example most appropriately falls into class IId rather than class IIa. Nevertheless, if one believes that the first arrest after release represents the crucial step in return to a criminal career, it is reasonable to focus only on that arrest. If the first arrest is for a property arrest, then the individual is no longer at risk of a first arrest for a nonproperty arrest, and vice versa. In the next chapter we shall see evidence that later arrests *are* different from first arrests.

TABLE 4 Estimates of Proportional Hazards Models for Different Arrest Types

TABLE 4

Estimates of Proportional Hazards Models for Different Arrest Types

Explanatory Variables	*1* *All Arrests*	*2* *Property*	*3* *Nonproperty*	*4* *Violent*	*5* *Other*
Education	−.022	−.006	−.033	−.086	.015
Financial aid (D)[a]	.108	.215	−.050	−.254	.140
Imprisoned for crime against person (D)	.080	.062	.087	.280	- −.037
Imprisoned for crime against property (D)	.449**	.889**	−.005	.300	−.221
Number of convictions for crimes against persons	−.124	−.089	−.145	.320	−1.29
Number of convictions for crimes against property	.232**	.242**	.226*	.361*	.092
Paroled (D)	.273*	.167	.414*	.173	.620*
Male (D)	.271	.203	.322	.214	.427
Age at earliest arrest	−.043**	−.051**	−.035*	−.023	−.045
Married (D)	.053	−.036	.167	.124	.187
Age at release	−.009	−.010	−.007	−.015	.000
N of arrests	340	192	148	69	78
N	955	955	955	955	955

a. (D) indicates dummy variable.
*Significant at .05 level.
**Significant at .01 level.

[p. 49 ↓] Results from estimating models for the two kinds of arrests are shown in columns 2 and 3 of Table 4. The effects of age at initial arrest and number of previous property convictions are approximately the same for each type of arrest. On the other hand, release on parole has a significant effect on nonproperty arrests but no effect on property arrests. Moreover, previous incarceration for a property crime substantially increases the risk of being arrested for a property crime but not for a nonproperty crime. Financial aid has no significant effect on either type of arrest.

Although we could stop the analysis at this point, further insight is obtained by subdividing the nonproperty arrests into two categories: violent crimes against persons and all other offenses. (This residual category consists, for the most part, of such relatively minor offenses as possession of marijuana, carrying a concealed weapon, and “neglect of family.”) A separate model is then estimated for each type of arrest, with results shown in columns 4 and 5 of Table 4. Note that only one variable**[p. 50 ↓]** has a significant effect for each arrest type. This is a consequence of the fact that overall significance levels will go down as the number of events becomes a smaller proportion of the total sample size. What is important here is that the effect of release on parole is large and significant for the “other” category but small and nonsignificant for violent crimes against persons. Similarly, while the number of previous property convictions has a significant effect on the hazard for violent offenses, it has no effect on other types of nonproperty offenses.

We see, then, that distinguishing different kinds of events can lead to different conclusions about the effects of explanatory variables. Similarly, the failure to distinguish among event types may produce misleading results. For example, in the model for all kinds of arrests, we found that those released on parole had a higher hazard for being arrested. Nevertheless, when we focused on specific types of events, the effect of parole status was significant only for relatively minor offenses.

Dependence Among Different Kinds of Events

The approach we have just described and applied for class IIa, competing risks, has one very important property. The type-specific hazard functions are defined in such a way that it is unnecessary to make any assumptions about dependence or independence among different kinds of events. To understand what this means, consider again the example of job terminations where we distinguish voluntary terminations from involuntary terminations. The two types would be dependent if, for example, persons who knew they were likely to be fired were more likely to quit, possibly to avoid the stigma of being fired. Or it could work the other way. Persons who wanted to quit might arrange to be fired in order to collect unemployment insurance. Neither case poses any problems for the kind of model which we have just considered.

While this is an attractive feature, it can be argued that the model solves the problem of dependence versus independence by simply defining it away. In fact, there are other approaches to competing risks in which the problem of dependence is crucial and, in some respects, insoluble. It can be shown, for example, that it is impossible to distinguish empirically models in which different kinds of events are dependent from a model in which they are independent (Tsiatis, 1975). While the mathematics of these different approaches is thoroughly developed, the interpretation and implications for empirical research are still controversial. (For a detailed discussion, see Kalbfleisch and Prentice, 1980: Ch. 7.)

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