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Beyond Logit and Probit: Cox Duration Models of Single, Repeating, and Competing Events for State Policy Adoption

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ABSTRACT

Since 1990, the standard statistical approach for studying state policy adoption has been an event history analysis using binary link models, such as logit or probit. In this article, we evaluate this logit-probit approach and consider some alternative strategies for state policy adoption research. In particular, we discuss the Cox model, which avoids the need to parameterize the baseline hazard function and, therefore, is often preferable to the logit-probit approach. Furthermore, we demonstrate how the Cox model can be modified to deal effectively with repeatable and competing events, events that the logit-probit approach cannot be used to model.

For a generation, political scientists have used the variation in policy among the American states to test theories of policymaking (e.g., Dye 1966 and Dawson and Robinson 1963). Since 1990, the seminal work of Berry and Berry (1990, 1992, 1994) has led scholars to focus on state policy adoption by collecting longitudinal data on the timing of each state's adoption of a given policy. Typically, these analyses use data that code a state from time t_0 at discrete time points, $t = 1, 2, 3, \ldots$ j, until the state adopts the policy. Hence, it is natural to measure the time until policy adoption and treat this quantity, or some function of it, as the response variable in statistical models of state policy adoption. The response variable is usually recorded as a binary sequence where 0 denotes nonadoption at a given time point and 1 indicates adoption. Using such response variables, duration models, or event history analyses, are now the standard in this area of research (Balla 2001; Berry and Berry 1990, 1992; Hays and Glick 1997; Mintrom 1997a, 1997b;

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Mintrom and Vergari 1998; Mooney and Lee 1995; True and Mintrom 2001). This kind of data set-up is what Beck, Katz, and Tucker (1998) refer to as binary time-series cross-sections (BTSCS).[1] The binary dependent variable in such state policy adoption analyses has led researchers to use logit or probit models routinely.

In this article, we address some implications for duration dependency of the use of logit or probit models to analyze policy adoption data. First, building on the recent work of Buckley and Westerland (2004), we consider the Cox model as an alternative modeling strategy for state policy adoption research. Specifically, the Cox model avoids the need to parameterize the baseline hazard function, making it preferable to the standard logit-probit approach. Next, we note that most duration models of policy adoption focus on single-spell processes, which not only leads to a loss of information but potentially to contradictory conclusions when comparing results of multiple-events models. Finally, we outline how the Cox model can be modified to deal effectively with two important multiple-events problems in state policy adoption research: repeatable and competing events.

SOME ISSUES REGARDING DURATION DEPENDENCY

Duration models of policy adoption are frequently motivated by questions of risk: Given that a state had not adopted a policy by time *t*, what are the chances that it would adopt it during time *t*? Usually, policy adoption data are observed at some discrete time, such as a legislative session or year, and they are usually treated as binary. If a state's time-until-adoption (T) for a given policy is assumed to be discrete, then adoption must occur at some observable time point. Under this assumption, the hazard rate for such a discrete-time process is:

$$h(t) = \Pr(T = t \mid T > t). \qquad (1)$$

That is, the hazard rate is the probability, or risk, of adopting a policy during some period, *t*. This natural interpretation of the discrete-time hazard rate as a probability has led to the widespread use of logit and probit models in policy adoption research. However, this approach makes an implicit distributional assumption regarding duration dependency. Such an assumption can lead to a logit or probit duration model being parameterized in terms of the exponential distribution, which suggests that the probability of a state adopting a policy is invariant to time.

To demonstrate this problem, we estimate a BTSCS logit model where the dependent variable is a state's adoption of restrictive abortion legislation after the 1973 *Roe v. Wade* decision (see Brace and Langer n.d. and Brace, Hall, and Langer 1999 and 2001 for fuller analyses of these data). The results from this model are shown in the first column of Table 1 (labeled Logit 1). Here, adoption of such a policy is treated as a function of six covariates. The covariates include a binary indicator denoting whether the state is in the *South*. *Ideological distance* measures the difference between the ideology score of a state's legislature and its high court, with higher scores indicating the legislature is more liberal than the court (Brace, Hall, and Langer 2001; Brace and Langer 2001). *Neighbor* indicates the proportion of bordering states that have adopted restrictive abortion legislation by that observation period. *Pre-Roe v. Wade* is the five-point Mooney and Lee (1995) index of pre-*Roe* abortion permissiveness, where a higher score indicates a state was more permissive in its abortion regulations. *Unified government* is scored 1 if the upper and lower chambers in the statehouse are controlled by the same party and 0 if not. Finally, *constitutional right* indicates whether a state had an explicit constitutional right to abortion.

The estimates in Table 1 are interpreted as in any logit model, where the sign on the coefficient indicates the direction of a change in the log-odds with a change in the covariate. The probability of state *i*'s adoption at time *t* is $\Pr(y_{it} = 1) = \lambda_i$, and the probability of nonadoption is $\Pr(y_{it} = 0) = 1 - \lambda_i$. Under the logit model, the log-odds are given by:

$$\log\left(\frac{\lambda_i}{1-\lambda_i}\right) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_k x_{ki}, \qquad (2)$$

Table 1. Logit BTSCS Models of State Adoption of Restrictive Abortion Legislation, 1974–93

Variable	Logit 1 Estimate (s.e.)	Logit 2 Estimate (s.e.)	Logit 3 Estimate (s.e.)
South	.62 (.46)	.60 (.42)	.63 (.39)
Ideological distance	–.06 (.13)	–.05 (.13)	–.06 (.12)
Neighbor	.10 (.22)	.06 (.22)	–.01 (.22)
Pre-Roe	–.19 (.08)	–.17 (.08)	–.17 (.08)
Unified government	.14 (.33)	.14 (.33)	.10 (.33)
Constitutional right	–.67 (.32)	–.57 (.30)	–.54 (.31)
Time	—	–.21 (.20)	6.95 (2.94)
Constant	–1.93 (.38)	–1.60 (.46)	–2.77 (.53)
N	418	418	418
Log-likelihood	–133.98	–133.33	–131.65

Note: Data are from Brace, Hall, and Langer 1999. Time in Logit 2 is log(t). Time in Logit 3 is a lowess function.

and the hazard rate is obtained by re-expressing (2) directly in terms of the probability,

$$\hat{\lambda}_i = \frac{e^{\beta' x}}{1 + e^{\beta' x}}$$

where $e^{\beta' x}$ is the exponentiated linear prediction (i.e., the log-odds) from the logit model. Thus, this model is directly analogous to an exponential model, where the hazard rate is flat with respect to time. That is, this model requires the assumption that, controlling for all the covariates in the model, the probability of adoption remains the same in each time period. To see this more clearly, reconsider the logit model. Suppose we estimate

$$\log\left(\frac{\lambda_i}{1-\lambda_i}\right) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i}, \qquad (3)$$

where x_{ki} are two covariates and β_0 is the constant term. If the $x_{ki} = 0$, then the baseline hazard under this model would be:

$$\lambda_i = h_0(t) = e\beta_0 \qquad (4)$$

which is a constant. Thus, the hazard probability is flat with respect to time. That is, the probability of a state adopting the policy is invariant to time, since the hazard rate at time t is identical to the hazard rate at any other time t_j.

This usually unrealistic restriction has commonly been made in state policy adoption research. Fortunately, this problem is easily resolved by including a duration dependency parameter(s) in the binary link model. There are a variety of approaches to including such a function of time in the model, including using log transformations, spline functions, locally weighted scatter-plot smoothing (lowess), and piecewise functions (Beck, Katz, and Tucker 1998; Beck and Jackman 1998; Mooney and Lee 1995). Additionally, temporal dummy variables can be used, although with many time points, this can result in many additional parameters (Mintrom 1997a; Mintrom and Vergari 1998; Mooney 2001).

In the second and third columns of Table 1 we re-estimate the abortion policy adoption model and include a covariate to account for duration dependency (*time)*. Logit 2 includes a log transformation of the duration time, and Logit 3 includes a lowess function of time. The model using the lowess function provides a better fit than either the exponential equivalent or the log (*time*) parameterizations in Logit 1 and Logit 2. Thus, estimates of the hazard probability—the fundamental quantity of interest—are affected by how duration dependency is accounted for in the model. This example also illustrates the more general point that the parameter estimates of a duration model can be sensitive to the specification of the duration dependency variable.[2]

THE COX DURATION MODEL

The Cox duration model has many features that can address the kinds of problems discussed above, making it especially amenable to modeling state policy adoption. This model departs most substantially from the logit-probit approach (or from other approaches using standard parametric models, such as Weibull, lognormal, and log-logistic models) in that the form of the baseline hazard rate is left unspecified. Thus, the hazard rate can take any form the data suggest (Collett 1994). This distinction makes the Cox model compelling because, if the form of duration dependency is incorrectly specified in a parametric model, "even the best-fitting model may not fit the data well enough to be useful" (Larsen and Vaupel 1993, 96). Moreover, as Blossfeld and Rohwer (2001) argue, social science theory is commonly agnostic as to the distributional form the baseline hazard rate should take. As such, a model where this component of the data need not be specified is highly preferable, all factors being equal. Because of this property, the Cox model is sometimes referred to as a semi-parametric model since the hazard rate is parameterized as a function of covariates but the distributional form of the hazard rate is not specified (Box-Steffensmeier and Jones 2004; Collett 1994).

A second advantage of the Cox model (and one that we discuss in more detail later) is that the model has been extended to easily accommodate research questions where multiple events can occur; for example, a state adopting different kinds of legislation. The logit-probit approach is not easily extended to this kind of problem. Finally, the Cox model has also been extended to handle the case of repeatable events; for example, a state adopting the same kind of policy multiple times. As with multiple events models, the logit-probit approach is not as flexible as the Cox model in handling repeatable events.

Under the Cox model, the hazard rate is given by:

$$h_i(t) = h_0(t) \exp(\beta' x), \tag{5}$$

where $h_0(t)$ is the baseline hazard function and $\beta' x$ are covariates and regression parameters. Although the baseline hazard rate is not directly estimated from the data, the covariate parameters are, using a partial likelihood approach (Cox 1972).[3] Substantively, this means that scholars can test how theoretically important covariates affect the chances that a state adopts a piece of legislation without having to make assumptions about the shape of the baseline hazard rate. Thus, analysts avoid potential biases that may result from using a parametric model with a faulty distributional assumption.

Even given the obvious advantage of eliminating the need to specify the distributional form of the hazard rate, one often-cited reason for avoiding the Cox model is the presence of "tied" events in duration data; that is, the co-occurrence of two or more events in the same observation period (Box-Steffensmeier and Jones 2004). For instance, multiple state legislatures may adopt the same policy in the same year. Indeed, such ties are common in state policy adoption research, given the discrete nature of the data involved; the presence of tied events makes it impossible to determine which observation experienced the event first in a given time period. As such, tied events pose estimation problems for the partial likelihood function because determining the structure of the risk set and the succession of events within a given time period is impossible.

Fortunately, several approximation methods have been developed to deal with the problems that tied events pose for Cox models. The Breslow method assumes that the size of the risk set remains the same regardless of the sequencing of events, the Efron method approximates how the risk set changes, and the average-likelihood method controls for possible sequences of events within a single time period (Box-Steffensmeier and Jones 2004). Each of these three approaches assumes that it is necessary to consider the sequence of the tied events. Another approximation, sometimes referred to as the exact-discrete method, results in an estimator that is equal to a conditional logit estimator, a model explicitly designed for truly discrete duration data (Box-Steffensmeier and Jones 2004; Therneau and Grambsch 2000).[4] Unlike the Breslow, Efron, and average-likelihood methods, the exact-discrete method assumes that the events occur simultaneously. For example, when two states adopt the same policy in the same year, this approach assumes that the adoptions occurred at the same time. Given these approximation methods, particularly the average likelihood and the exact-discrete approximations, the issue of tied events is no longer an important applied issue.

AN EXAMPLE OF A COX DURATION MODEL

To illustrate this application of the Cox model, we re-estimate the model of abortion law adoption from Table 1 and present the results in Table 2. The coefficient estimates in this table are expressed in terms of the hazard rate. A positive coefficient indicates that the hazard rate increases in value as the covariate increases, implying that the time-until-adoption is decreasing. A negative coefficient indicates a decreasing hazard rate, implying that the time-until-adoption is increasing. So, the negative coefficient for the index of pre-*Roe* abortion permissiveness suggests that pre-*Roe* permissiveness led to a lower chance of a state adopting post-*Roe* restrictions. We find that southern states are significantly more likely to adopt restrictive abortion legislation, while states having a constitutional provision permitting abortion are predictably far less likely to adopt restrictive abortion legislation. Finally, these results suggest that there is no relationship between a state's adoption of restrictive abortion legislation and its neighboring states' adoption of such legislation. Furthermore, there is no apparent effect of the ideological distance between the legislature and the court on legislation adoption, although we will return to this result later.

A comparison of the Cox results in Table 2 with the logit models in Table 1 shows differences in the parameter estimates and associated standard errors. For example, in the logit model with the lowess duration dependency parameter (Logit 3), the coefficient estimate for the constitutional right covariate is much smaller than the corresponding estimate in the Cox model and has a much lower z-ratio (1.74 in the logit model versus 2.98 in the Cox model). A similar pattern is seen for the pre-*Roe* coefficients. These distinctions are attributable to two features of these models: 1) differences in the partial likelihood estimator for the Cox model and the maximum likelihood estimator for the logit models, and 2) differences in how the baseline hazard is accounted for in the Cox and logit models. The possible sensitivity of parameter estimates to how duration dependency is parameterized (Box-Steffensmeier and Jones 2004; Collett 1994) can lead to differences between Cox estimates and estimates from other duration models. Because parameter estimates are

Table 2. Cox Single-Event Duration Model of the Adoption of Restrictive State Abortion Legislation, 1974–93

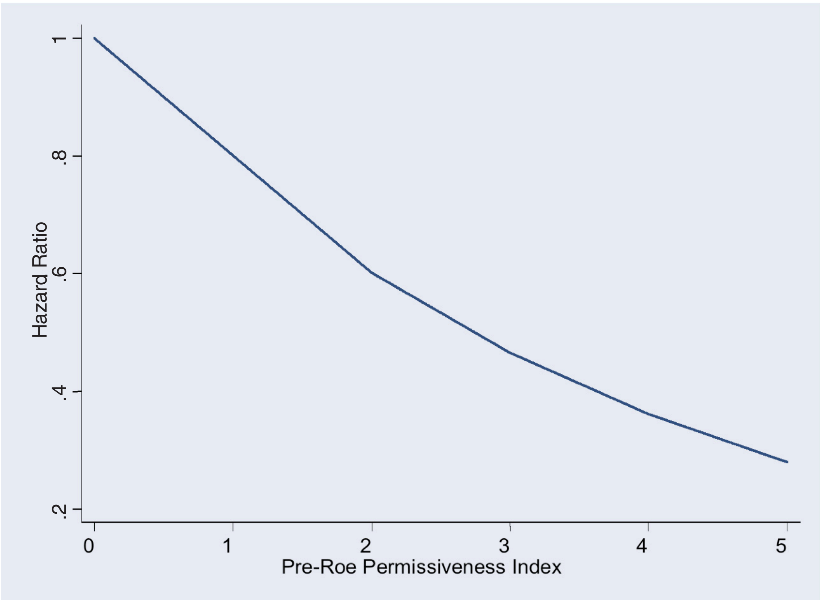
Variable	Estimate (s.e.)
South	.82 (.43)
Ideological distance	–.14 (.12)
Neighbor	.24 (.23)
Pre-Roe	–.25 (.09)
Unified government	–.01 (.34)
Constitutional right	–1.31 (.44)
N	418
Log-likelihood	–172.84

Note: Data are from Brace, Hall, and Langer 1999.

sensitive to the way that the duration dependency is accounted for, the Cox estimates are preferable as one does not have to specify the functional form of the baseline hazard rate.

We can interpret the estimated magnitude of the effects of the covariates in the Cox model by comparing estimated hazard ratios, which are simply the exponent of the coefficient multiplied by a value for the covariate. For example, for southern states, the estimated hazard ratio is $\exp(.82 \times 1) = 2.27$, while for non-southern states, it is $\exp(.82 \times 0) = 1$. This implies that southern states are estimated to be 2.27 times more likely to adopt restrictive abortion legislation than non-southern states. The hazard ratio may also be used to describe the covariate effects for continuous covariates, but the effect should be evaluated at a range of values of the covariate since the effect may be different at different values. Consider how the hazard changes as a function of the pre-*Roe* permissiveness index. In Figure1, we display the computed change in the hazard across the range of this covariate. The

Figure 1. Estimated Impacts on Abortion Law Adoption Hazard Rate of Pre-*Roe* Permissiveness



Note: The figure illustrates the estimated effect on the hazard rate of adopting a restrictive abortion law in a state of pre-*Roe* regulation permissiveness, based on the Cox model in Table 2.

downwardly sloping line indicates that higher levels of pre-*Roe* permissiveness is related to a decrease in the hazard. Thus, legislatures in states where abortion rights were most permissive before *Roe* are about 3.5 times less likely to adopt restrictive abortion legislation than legislatures in states with the most restrictive pre-*Roe* regulations (i.e., 1/.28).

These results should motivate scholars to consider the Cox model in state policy adoption research. As we noted, the widely-used logit and probit models produce exponential-equivalent models. Accordingly, even if one accounts for duration dependency by including a function of time in the model, the form of the baseline hazard must still be specified in some way. But perhaps the most important advantage of the Cox model over the logit-probit BTSCS approach to modeling policy adoption is that the Cox model can be extended to account for more complicated event structures. Repeating, multiple, and competing events can easily be theorized to occur in the state policy adoption process, but they are not often dealt with in the policy adoption literature because the logit-probit BTSCS approach cannot be used to model them. It is to this advantage of the Cox model that we now turn.

MULTIPLE EVENTS DATA AND STATE POLICY ADOPTION RESEARCH

The most common duration modeling strategy in the state policy adoption literature focuses on so-called "single-state" processes (Box-Steffensmeier and Jones 2004) or the occurrence of a singular event, such as the adoption of a single type of legislation. Furthermore, after the event's occurrence in an observed unit (for example, a state), the unit is assumed to exit the risk set. That is, the unit is no longer at risk of having that event. In the language of state policy adoption, such models imply that the researcher is interested in the adoption of a single policy only once in a given state. Once a state government adopts this policy, it is assumed to be no longer at risk of adopting other policies of the same or similar type at a later time period. From this perspective, the only event of interest is the first event.

Of course, this is only the simplest of theoretical event models. First, consider the possibility that multiple events could occur at different times within an observation period. In the context of state policy adoption research, this means that a state might adopt more than one policy in a given policy domain. For example, in the policy domain of abortion restrictions, a state could adopt several different kinds of abortion restrictions. Models that account for such multiple events are sometimes called repeatable-events models (Box-Steffensmeier and Jones 2004; Box-Steffensmeier and Zorn

2002; Wei and Glidden 1997). Second, state policy adoption research typically treats all policies adopted in a given analysis as equal. But certainly many different types of policies could be adopted within a given domain. Duration models that account for the occurrence of different kinds of events are sometimes called competing risks models (Box-Steffensmeier and Zorn 2002; Collett 1994; Gordon 2002). In this section, we consider how the Cox model can be extended to model these more complex processes in the context of policy adoption analysis.

MODELING REPEATING EVENTS

States may adopt multiple policies in the same legislative domain. For example, in Table 3 we reproduce a portion of a dataset that records when and whether a state adopted obscenity legislation each year, 1991–98.[6] Such legislation could relate to any aspect of obscenity, such as the regulation of pornography or the adult entertainment industry. Typical of state policy adoption datasets, the unit of analysis is a state-year, and the event is measured discretely and at each time period coded as either observed or not observed. Table 3 shows that no such event occurred in Colorado during the

Table 3. Example of a Repeatable Events Dataset: Obscenity Legislation Adoption, 1991–98

Year	State	Event	Overall Time	Conditional Time	Risk Sequence
1991	CO	0	1	1	1
1992	CO	0	2	2	1
1993	CO	0	3	3	1
1994	CO	0	4	4	1
1995	CO	0	5	5	1
1996	CO	0	6	6	1
1997	CO	0	7	7	1
1998	CO	0	8	8	1
1991	FL	0	1	1	1
1992	FL	1	2	2	1
1993	FL	1	3	1	2
1994	FL	0	4	1	3
1995	FL	0	5	2	3
1996	FL	1	6	3	3
1997	FL	0	7	1	4
1998	FL	0	8	2	4

Note: Laura Langer made these data available to us. This is a subset of the 50-state dataset analyzed in Table 4.

study period (i.e., the event indicator is coded 0 each year), indicating that Colorado goes eight periods (years) without any policy adoption.[7]

Contrast Colorado with Florida in Table 3. In the second risk period (1992), Florida adopts a piece of obscenity legislation, followed by another piece of obscenity legislation in the third observation year (1993). In the column labeled conditional time, we note that the timing of this second event, conditional on the previous event, is 1, indicating that the second event occurs in the first risk period following the first event. This conditional clock is reset to 0 after each event occurs. Florida passes no further obscenity legislation until 1996, when it adopts yet another such law. In terms of the overall duration time in the study period, this event occurs in the sixth observation year (t_6); in terms of the conditional time, i.e., the time since the last event, this event occurs at $t_C = 3$, where the subscript C denotes this timing is conditional. After this third piece of legislation is adopted, the conditional time counter resets. Two years pass before the end of the observation period, and no further legislation is adopted. Hence, $t_C = 2$ at the end of the study period.

Finally, the risk sequence column of Table 3 contains information on the ordering of events for which the state is at risk. Because Colorado remains only at risk of adopting its first piece of obscenity legislation, the risk sequence is coded 1 for the entire observation period. On the other hand, Florida is only at risk of adopting its first piece of legislation for two periods. It then becomes at risk of adopting its second piece of obscenity legislation, and after its second adoption, it becomes at risk of a third adoption. Florida's risk sequence is therefore coded to reflect its repeated adoption of obscenity legislation.

Repeated-events data, such as in Table 3, are quite common substantively, but they pose several challenges for standard duration modeling. First, in the BTSCS approach, an implicit assumption is made that the first event will be representative of all events. Second, analyzing only the first event discards information unnecessarily. In our example, a BTSCS model would exclude Florida from the dataset after first adoption, even though that state repeatedly adopts obscenity legislation and, thus, remains at risk of doing so throughout the study period. A BTSCS model neglects all of the information that could be gained from analyzing the covariates of these subsequent events.

Thus, in repeated-events processes, the unit of observation (e.g., the state) never leaves the risk set. How, then, can a repeated-events process be modeled? Fortunately, modeling repeated events can be done precisely with only a slight modification to the standard Cox model. While several such modifications have been proposed (Andersen and Gill 1982; Therneau and

Grambsch 2000; Wei, Lin, and Weissfeld 1989; Box-Steffensmeier and Zorn 2002), we focus on the type of modification that is most applicable for state policy adoption data: the conditional gap time model.[8]

The gap referred to here is the time interval between successive repeated events. Under this model, the duration time is assumed to reset after the occurrence of each event. Thus, after the first event, the case becomes at risk for the second event, at which time the duration time counter is again reset. This model is "based on the idea that an observation is not at risk for the *k*th event until the k–1 event has occurred" (Box-Steffensmeier and Jones 2004, 161). To account for the ordering of events, the model is stratified by the event number, which corresponds to the risk sequence indicator in Table 3. Defining T in a duration dataset in terms of the conditional gap time (in Table 3, conditional time) and estimating a Cox model that stratifies on event number (in Table 2, risk sequence) (Box-Steffensmeier and Jones 2004; Box-Steffensmeier and Zorn 2002) produces a conditional gap time Cox model. By stratifying on the event number, the baseline hazard may vary by event number, while the covariate parameters remain the same across the ordered events. Hence, unobserved heterogeneity among different event numbers is accounted for in the model in *k* baseline hazards, and estimates of the covariate parameters remain.[9] Moreover, stratification preserves the ordering of events, whereas nonstratified estimates assume that the ordering of events is unimportant.

To develop an example of the conditional gap time model, we use the data on obscenity legislation adoption illustrated in Table 3. This dataset is replete with multiple events. Across the 50 states, 94 events occurred during the study period, with an average of just under two events per state. Clearly, estimating a single-event, logit-probit, BTSCS model of this process would result in a considerable loss of information. Our models of obscenity legislation adoption include seven covariates (Table 4)[10]: the percentage of the state's population who claim to be fundamentalist Protestants, a binary indicator denoting southern states, the state's murder rate, the percentage of women in the state legislature, the percentage of college-educated adults in the state, and measures of the state's citizen and legislative ideology (Brace, Hall, and Langer 1999).[11]

To illustrate the implications of using different statistical models with repeated-events data of state policy adoption, we estimated three separate Cox models of state obscenity law adoption (Table 4). The first column in Table 4 presents estimates for a standard single-event Cox model (as described above), which accounts for only the first event in each state. Thus, instead of all 94 adoptions, this model only takes into account 37 adoptions, using

Table 4. Cox Conditional Gap Time Model: Obscenity Legislation Adoption, 1991–98

	Single-Event Model	Non-Stratified Events Model	Repeated Events Model
Variable	Estimate (s.e.)	Estimate (s.e.)	Estimate (s.e.)
Fundamentalist	–.02 (.21)	.18 (.13)	.22 (.10)
South	.79 (.56)	.19 (.46)	.04 (.42)
% college educated	.11 (.07)	.12 (.06)	.12 (.05)
Legislative ideology	–.07 (.01)	–.03 (.01)	–.02 (.01)
Citizen ideology	.09 (.02)	.05 (.02)	.04 (.01)
% women in legislature	–.07 (.04)	–.01 (.03)	.00 (.02)
Murder rate	.24 (.06)	.16 (.04)	.18 (.04)
N	226	400	400
Log-likelihood	–147.23	–447.21	–334.18

Note: The first column of estimates are from a Cox single-event model, the second are from a Cox independent-events model, and the third are from a stratified Cox model of repeated events. These data on state adoption of obscenity legislation were provided by Laura Langer.

less than 40 percent of the actual events in the study period in this analysis. This model represents the approach of most scholarship on state policy adoption, which focuses only on the first adoption. While this approach may be warranted theoretically for some processes, if it is done merely out of convenience, the results may be biased and inefficient estimates of the model parameters (Box-Steffensmeier and Jones 2004; Wei and Glidden 1997).

To illustrate these potential negative effects, consider the third column of Table 4 that estimates a Cox conditional gap time model of repeated events. Here, we stratify on the event number, maintaining information on the ordering of events. Because we model the repeatability of events directly, all 94 events enter the analysis. Comparing the single-event model estimates (first column) with the repeated-events model estimates (third column) shows substantial differences. The single-event model suggests that the prevalence of fundamentalist Protestants in a state has no impact on the adoption of obscenity legislation, while the conditional gap time model leads to the conclusion that states with more fundamentalists are more prone to adopt this kind of legislation. In addition, the single-event model suggests that the percentage of women in the state legislature is associated with a lower probability of a first adoption of obscenity legislation, while in the repeated-events model, the percentage of women in the legislature has no statistically discernible impact. Finally, we find that while they are statistically significant in each model, the estimated magnitudes of the effects of the murder rate and ideology covariates are smaller in the repeated-events model than in the single-event model.

As a result, our estimates of the impacts of these covariates on the adoption of this type of legislation vary depending on how the event history process is modeled and our resulting conclusions about the political process differ substantially between these models. Estimating a single-event model when the event is repeatable results in a loss of information. Because the conditional gap time Cox model uses all of the available information on the events and their ordering, we strongly prefer this model to the single-event Cox model in this case.

Finally, for completeness, we estimated a nonstratified Cox model of these obscenity law adoptions, which ignores the ordering of events (second column, Table 4). In this model, because the data are not censored after an adoption, information on all 94 events is used, but information on the ordering of the events is not included in the analysis and is assumed to be unimportant. Thus, the baseline hazard function is assumed to be identical for all events that occur in a state, regardless of the order in which they occur. This conflicts with the stratified model (column three) where the baseline hazard function for each event number takes its own shape. In comparing the log-likelihoods of these models, the stratified model provides a superior fit to the nonstratified model, even though both use information on the repeatable events. The covariate estimates are similar across the two models, although they are certainly not identical. For instance, fundamentalism is related to the adoption of obscenity legislation in the stratified model to a statistically significant degree; whereas it is not in the nonstratified model.

In summary, the Cox conditional gap time model provides state policy adoption researchers a way to model repeatable adoptions that requires only slight modifications to the duration times and the definition of the risk set from a Cox single-event model. Such an approach allows researchers to bypass fixes to the BTSCS approach, such as the inclusion of an event counter (Beck, Katz, and Tucker 1998), which can limit validity (Therneau and Grambsch 2000; Wei and Glidden 1997). Moreover, the use of the logit-probit BTSCS model in this setting still does not obviate the problem posed by duration dependency discussed in the previous section. The Cox model's ability to estimate, rather than assume, duration dependency is even more beneficial in the repeated-events setting, since the baseline hazard may vary substantially over the *k* ordered events.

COMPETING EVENTS

The tendency to focus on single events in state policy adoption research is problematic not only with repeated events but also with multiple, or competing, events. Such processes occur when there is a risk of experiencing one of *m* distinct events whose risks are related. To illustrate, consider our data on the adoption of restrictive abortion policy. In the Cox model in Table 2, we made no attempt to distinguish among the different types of legislation that could have been adopted. Defining events so broadly may be appropriate for modeling a process when the researcher is interested in the adoption of any kind of legislation within some broad domain. However, it may be more theoretically interesting and substantively appropriate to model some processes by defining events in a more refined way. For example, in the post-*Roe* era, Brace and Langer (2001) argue that state policies restricting abortion tend to fall into four categories: policies requiring spousal consent, policies requiring informed consent, policies requiring parental consent, and policies limiting funds for providers of abortions. Modeling the adoption of policies in each of these categories separately may allow the researcher to test more subtle hypotheses of policymaking.

We discuss two variants of the Cox model that can be used to model competing events.[12] First, consider a model similar to the Cox conditional gap time model. A policy adoption process assumes that states are at risk of adopting one of *m* distinct policies, such as the four kinds of restrictive abortion policies Brace and Langer (2001) define. Because states may adopt multiple policies, they never leave the risk pool. Furthermore, the adoption of one policy does not preclude the adoption of another type of policy in the same time period. Thus, if a state adopted policy *m* in time period *t*, it would still be at risk of adopting any of the remaining $m - 1$ policies in time *t*.

For many policy domains, this is a plausible condition. Certainly, a state legislature could adopt both a law requiring spousal consent for abortion and one requiring informed consent in the same legislative session. Fortunately, accommodating such a competing-events scenario entails a relatively straightforward modification of the standard Cox model. Under this variant of the Cox model, each state is assumed to be at risk of adopting any of *m* policies in each time period. There are no restrictions on which of the policies a state could adopt or when it could do so. Since the state is in the risk set for each of the policies, each state appears *m* times in the dataset for each time period, once for each possible event (Cleves 1999). A stratified Cox model is then applied to such a dataset, where the stratification variable indicates the event type. This assumes that the covariate effects are the same for each event type, but the baseline hazard for each *m* policy type event can be unique. Thus, while this stratified Cox model gives estimates of a single set of covariate parameters, the *m* baseline hazard estimates can be retrieved from these estimates (Collett 1994; Box-Steffensmeier and Jones 2004). In this sense, stratification serves the same purpose as in the repeating events model, in that any heterogeneity not accounted for by the covariates is accounted for in the *m* baseline hazards. As Box-Steffensmeier and Jones (2004, 176) note, "this approach to the competing risks problem may be appropriate for many kinds of competing risks problems in political science, especially where the occurrence of an event does not imply the observation exits the sample." This situation commonly occurs in state policy adoption research using duration data with competing events.

To illustrate, consider a Cox stratified competing risks model of state adoption of restrictive abortion legislation in which we account explicitly for Brace and Langer's (2001) four types of restrictive abortion policies. Table 5 presents these results (column 1) and a single-event Cox model (column 2) that does not discriminate among event types. The covariates used in this analysis are the same as those used in Tables 1 and 2.

Does accounting for competing risks improve our statistical estimates in this example? Comparing the stratified competing risks estimates and the single-event estimates in Table 5, we see some substantial differences. The stratified model yields a smaller coefficient estimate for the South covariate, implying that once the event type is accounted for (through stratification), the impact of this covariate on the probability of adopting this legislation is attenuated. Moreover, after stratifying on the event type, we find that the probability of ideological distance being related to policy adoption is greater in the non-stratified model. A similar difference is seen with the unified government covariate. Furthermore, while statistically significant in both

Table 5. Comparing Competing Risks and Single Event Cox Models of State Adoption of Restrictive Abortion Legislation, 1974–93

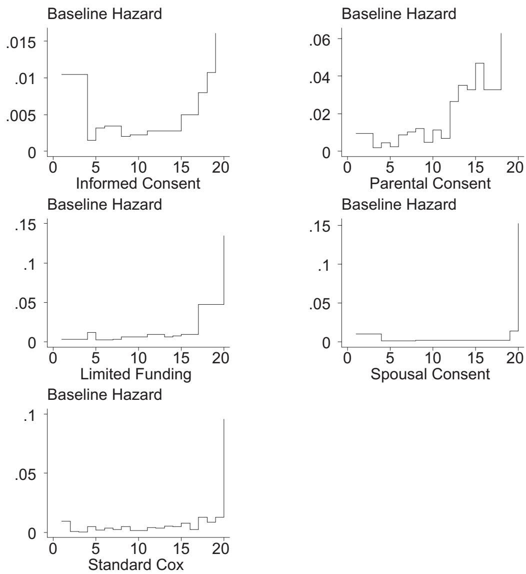
	Stratified Competing Risks Model	Single-Event Model
Variable	Estimate (s.e.)	Estimate (s.e.)
South	.66 (.26)	.82 (.43)
Ideological distance	–.14 (.07)	–.14 (.12)
Neighbor	.11 (.16)	.24 (.23)
Pre-Roe	–.19 (.06)	–.25 (.09)
Unified government	.11 (.22)	–.01 (.34)
Constitutional right	–.92 (.28)	–1.31 (.44)
N	2554	418
Log-likelihood	–455.23	–172.84

Note: Data are from Brace, Hall, and Langer 2001. Both models are semi-parametric Cox models.

models, the size of the pre-*Roe* estimated coefficient is smaller in the stratified model than in the non-stratified model.

Just as important as the differences in the coefficients, recall that with a single-event model, the baseline hazard is constrained to be identical over the four possible event types, while not in the competing risks model. In Figure 2, we display the baseline hazard estimates computed from the models presented in Table 5. The top four panels are the estimated hazards for the four types of abortion policy from the stratified model, and the bottom panel is the baseline hazard estimate for the single-event model. Clearly, the policy-specific baseline hazards differ markedly from each other and the single-event estimates. This difference is especially true for the parental consent policy, where the hazard is rising fairly steadily over time. While we do not advocate ascribing much substantive meaning to baseline hazard functions, Figure 2 shows considerable heterogeneity for this set of policies. Allowing variation with the stratified competing risks model produces a model superior to one where the baseline hazards are constrained to being equal across event types.

Figure 2. Estimated Baseline Hazards from State Abortion Law Adoption Competing Risks Models



Note: This figure gives the estimates of the Cox baseline hazards from the models in Table 5. The first four panels are estimated from the stratified competing risks model, and the bottom panel is estimated from the single-event model.

An alternative competing risks model allows the covariate parameters to vary over the m events, unlike with the stratified Cox model. Such a model allows the test of a hypothesis that, for example, states with a more liberal legislature than court support parental consent laws yet oppose limiting funding for abortion providers. This is done by estimating a Cox model variant for each mth event, while treating the remaining $m - 1$ outcomes as being right-censored. Doing this for each policy type produces m Cox models with $(k \times m)$ covariate coefficient estimates, where k is the number of covariates. Crowder (2001), David and Moeschberger (1978), and Hougaard (2000) demonstrate that this modeling strategy effectively decomposes the overall likelihood (or partial likelihood) into m subcontributions, each corresponding to the unique event type (see Diermeier and Stevenson 1999 for a political science example).

We estimate such a type-specific competing-hazards model with the state abortion law adoption data and present the results in Table 6. The utility of this model over the stratified model in Table 5 is that estimating coefficients for each of the m policies allows us to evaluate hypotheses of difference between the impacts on adopting these policies. In Table 6, each column corresponds to one of the m policies a state could adopt. The parameter estimates suggest considerable variability in the impact of some of these covariates across the policy types. For example, ideological distance is strongly related to the adoption of parental consent laws but is not related to the adoption of any other type of policy. Likewise, the pre-*Roe* permissiveness index is strongly related to the adoption of informed consent and spousal consent laws, moderately related to the adoption of a parental consent law, and not

Table 6. Cox Type-Specific Competing Risks Models of State Adoption of Restrictive Abortion Legislation, 1974–93

	Informed Consent	Parental Consent	Limited Funding	Spousal Consent
Variable	Estimate (s.e.)	Estimate (s.e.)	Estimate (s.e.)	Estimate (s.e.)
South	.32 (.59)	.31 (.46)	.93 (.49)	.35 (.63)
Ideological distance	–.17 (.16)	–.32 (.14)	.08 (.14)	–.05 (.18)
Neighbor	.05 (.36)	–.05 (.28)	.01 (.31)	.38 (.36)
Pre-Roe	–.26 (.14)	–.14 (.10)	–.12 (.11)	–.29 (.16)
Unified government	.34 (.47)	–.24 (.36)	.21 (.44)	–.34 (.53)
Constitutional right	–1.06 (.65)	–.93 (.47)	–.82 (.53)	–.66 (.63)
N	386	386	386	386
Log-likelihood	–132.75	–222.67	–157.08	–91.25

Note: Data are from Brace, Hall, and Langer 1999.

related to limiting funding for abortion in a state. Perhaps this suggests that consent legislation is viewed as more restrictive than funding legislation, with the impact of the pre-*Roe* environment on abortion rights having its strongest effects on the adoption of the most restrictive legislation. Finally, the results indicate that states with a constitutional right to abortion are far less likely to adopt any abortion restrictions.

Given that the effects of the covariates seem to be different for different types of events, this type-specific model provides evidence that the stratified Cox model assumption of equal covariate effects is at least sometimes unwarranted. However, the type-specific model does have drawbacks. Because the overall hazard function is partitioned into *m* subhazards, the estimates from type-specific models may be sensitive to the number of events that are observed in each category, especially if the observed number of events in a given category is small (Box-Steffensmeier and Jones 2004). With few events per category, the Cox model has less information with which to estimate the coefficients. In our abortion legislation example, this concern may be relevant, since there are only 17 spousal consent events in the dataset.

The major advantage of the type-specific competing-risk model is that it takes advantage of the potential for different kinds of events to have different baseline hazard rates and uses this information to inform the coefficient estimates. If one has reason to think that the influences on the adoption of different kinds of events in a policy domain are different, then the type-specific model of competing events is preferable. While, the choice between the stratified and the type-specific competing risks models may be regarded as an empirical question, theory may indicate the use of one model over the other.

CONCLUSION

We have presented some alternative strategies for modeling state policy adoption using duration models that allow a researcher to test more and richer hypotheses than those allowed by the current standard BTSCS models using binary links like logit and probit. The Cox models we discuss do not require the parameterization of the baseline hazard function. While researchers are typically most interested in these models' covariate parameter estimates, these can be highly sensitive to the baseline hazard parameterization, so a model that leaves this function unspecified will often be preferable to the standard logit-probit approach. And since Cox estimates are easily interpretable in terms of the hazard rate, the same kind of substantive information that is produced by a binary link model is also produced by a Cox model.

Perhaps the most important modifications the standard Cox model can allow a researcher is the flexibility to model various event processes, especially those involving multiple events. In many policy domains, states can adopt and re-adopt legislation. States may also adopt multiple kinds of legislation. Because of the reliance on BTSCS models, the policy adoption literature has been constrained to focus on single-event models. Thus, apart from a lack of efficiency and potential bias in estimating parameters, the use of BTSCS models restricts the ability of researchers to test models of the policy adoption process that are richer and more realistic than a simple single-event process. The variants of the Cox model that we have introduced allow researchers to test such models.

Not surprisingly, there are several other nuances of, and issues with, Cox models that we have not had space to cover in this article. For example, researchers should be aware of the proportional hazards assumption and test for it, but such tests can be easily applied and resolving violations of this assumption is quite straightforward (Box-Steffensmeier and Zorn 2001).[13] Furthermore, we did not discuss several other modeling strategies that could be fruitfully applied to policy adoption data. Among these are flexible parametric models (Royston and Parmar 2001, 2002), dependent-risks models (Gordon 2002), and frailty or random-coefficients models (Box-Steffensmeier and Jones 2004). Despite these omissions, the problems we have discussed and the solutions we have proposed expand the menu of modeling strategies for state policy scholars that should help broaden our understanding of state policy adoption dramatically.

ENDNOTES

We would like to thank Paul Brace, Fred Boehmke, Patrick Brandt, Laura Langer, and Chris Zorn for comments on various versions of this article.

1. Allison (1982, 1984), Beck, Katz, and Tucker (1998), and Box-Steffensmeier and Jones (1997, 2004) demonstrate that BTSCS data are equivalent to duration data. In these studies, this equivalency would seem to hold only for single-events data (i.e., when only one event can occur). However, as we discuss in this article, multiple and competing events can still be incorporated into the BTSCS framework.

2. This is also an issue in the application of standard parametric models such as the exponential, Weibull, or log-logistic model (Box-Steffensmeier and Jones 2004; Collett 1994).

3. For a full consideration of partial likelihood estimation, see Cox 1972 or Collett 1994.

4. In Stata, one references the exact-discrete estimator by specifying the option, exactp. One obtains the same results by specifying the model as conditional logit, although

modifications to the input dataset may be needed in some applications. Furthermore, note that the complementary log-log model (cloglog) is isomorphic to the Cox model (Allison 1995). That is, the cloglog model is equivalent to a continuous time Cox model when the data have been discretized (i.e., formulated as a binary sequence). However, for truly discrete data, like that usually analyzed in the state policy adoption literature, we recommend the exact-discrete approximation (i.e., the conditional logit approach) over the cloglog approach for several reasons (Box-Steffensmeier and Jones 2004). First, since the cloglog is a natural extension of a continuous time model, heavily tie-laden data can pose a problem for it (Therneau and Grambsch 2000). Second, the conditional logit model is derived as a discrete-choice model, making it better suited for discrete-time processes. Third, although parameters from a cloglog model give rise to a proportional hazards interpretation (like the standard Cox model), the issue of duration dependency (i.e., characterizing the baseline hazard) remains a problem.

5. A more richly specified model of the adoption of these laws might resolve this issue. For example, including a covariate for partisan control of the statehouse might help explain this result. However, such data were not available for the analysis used in this illustration.

6. These data were made available to us by Laura Langer.

7. Hence, this state is fully right-censored, that is, as of the last observation period, the observation had yet to experience the event (Box-Steffensmeier and Jones 2004).

8. These modifications of the Cox model for repeating events are derived from work done on counting processes (Andersen and Gill 1982; Fleming and Harrington 1991; Therneau and Grambsch 2000). Counting process theory has also led to extensive developments on Cox model diagnostics (Therneau and Grambsch 2000). Therefore, while the modifications of the Cox model discussed are relatively straightforward, requiring little more than redefining the composition of the risk set, the statistical theory from which these simple modifications are derived is extremely rich and important for reasons far beyond the issues dealt with in this article.

9. This unobserved heterogeneity explains the baseline hazard function variation across the repeated events. Ignoring the repeatability of events leads to the assumption that the baseline hazard function remains identical for all events. Furthermore, ignoring the ordering of the repeated events imposes a strong independence assumption on the data, namely that all subsequent events are independent of all previous events. Both of these assumptions are certainly restrictive and usually wrong. The modified Cox model we discuss avoids these problems.

10. All of the models in Table 4 account for clustering using the Lin-Wei variance estimator (Lin and Wei 1989).

11. See Brace, Hall, and Langer (1999) for a discussion of the rationale and substantive hypotheses behind including these variables in our model.

12. The logit analog to the competing risks model is the multinomial logit model. We do not discuss this model explicitly, but the same issues raised with the single-event logit-probit model also pertain to multinomial logit modeling of events data. The literature on competing risks problems is vast, and a number of models have been proposed for these kinds of data (Gordon 2002). We focus only on extensions of the Cox model.

13. In all of the Cox models we have presented, we assessed the proportional hazards assumption using Harrell's ρ and in each case, we found this assumption to hold.

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