Approaches to Modeling the Adoption and Modification of Policies with Multiple Components

(Preliminary Draft - Caveat Laudator)

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ABSTRACT

Recently, scholars have begun to move beyond the dichotomous dependent variable — indicating whether a state adopts a policy or not in a given year — usually employed in EHA. In particular, recent papers have devoted increasing attention to the components of policies that states adopt. In this paper I discuss a variety of models that have been employed to analyze the adoption and modification of policies with multiple components, including OLS, event count models and more advanced forms of event history analysis. Each of these models corresponds to a different substantive question and may be appropriate for testing some hypotheses and not others. Further, a variety of complications arise in the this context, which I also discuss. In particular, the interrelatedness of these components may lead to violations of assumptions of independence both over time and across components. For example, future policy modifications may be contingent on whether previous components have been adopted. The different models are illustrated by studying state adoption of various obesity-related measures.

1 Introduction

For the last sixteen years the standard approach to modeling state policy innovation has been event history analysis (EHA).[1] This approach has proven to be extremely flexible and has allowed scholars to answer a variety of important research questions. The methodology has become so widespread that cataloging the breadth of its applications would be a sizable task in its own right. To some degree, however, the field of political science has reached a point of diminishing marginal returns from the standard, discrete time-until-adoption study. That is, while there certainly remain theoretical advances that can yet be made within this framework (see, e.g., Berry and Baybeck 2005; or Shipan and Volden 2006), as the literature moves forward scholars are developing hypotheses that are not necessarily amenable to testing within the standard EHA approach.

Some of these newer hypotheses, including the two examples given above, can be tested with the tried and true EHA model. Yet there are at least three reasons that have led researchers in this area to push against the confines of the discrete time-until-adoption EHA with the state-year as the unit of observation. First, there are theoretical reasons. In order to move beyond the usual number-of-neighboring-states measure of policy diffusion pressures, Volden (2006) devises an approach that allows him to model diffusion processes between all pairs of states. Boehmke and Witmer's (2004) study of Indian gaming adoptions is able to break apart the distinct effects of having and using the direct initiative process on policy adoption by modeling the number of gaming compacts reached by each state. These studies would not possible with a standard EHA model.

Second, there are measurement-motivated reasons. Many policies are difficult to fit into the dichotomous requirements of EHA, even excluding policies such as expenditures that are measured

[1] I use the publication of Berry and Berry's (1990) article as the inception of the EHA era in political science.

in a continuous fashion. While some policies, like whether a state has a lottery (e.g., Berry and Berry 1990), are easily approximated with a discrete indicator, others are not. For example, does a state have good pain-management policy if it only allows three of the eight measures advocated by the Pain Policy Studies Group (Imhof 2006)?

Third, there are policy-motivated reasons. States may revise an existing policy or they may expand its scope in subsequent years. States consistently adjust their policies to reflect shifting needs among their citizens, to respond to technological changes or in order to incorporate new advances developed in other states. Shifts in the political climate or the partisan control of government may also lead states to revisit their earlier policy decisions. States may also take an incremental approach to adopting policies with uncertain consequences or political support. Thus states may be willing to negotiate gaming agreements with Indian nations that allow pari-mutuel wagering, then expand them to permit specific card games, then perhaps allow all house-banked games of chance; or they may negotiate agreements with only a few Indian nations at first and then with additional tribes at a later date.

One of the consequences of these many issues is that scholars have begun to move beyond the dichotomous dependent variable — indicating whether a state simply adopts a policy or not in a given year — usually employed in EHA. One way that they have done this is by focusing on the multiple components that a given policy encompasses. These components may be complementary or alternative ways to accomplish a given policy objective; states may adopt none, some or all of them in a given year and may adopt additional components in later years. Examples include the eight components of pain management policy recommended by the Pain and Policy Studies Group in its 1998 report, the nine components of state medical malpractice reform studied by Yackee (2005), and the three components of anti-smoking policy studied by Shipan and Volden

(2006, shipan-volden-cities).

Considering the details of policy adoption by the presence or level of specific components has both methodological and substantive advantages. Substantively, their consideration allows us a richer understanding of the heterogeneity of state policy and reflects the variation in the methods through which states seek to accomplish their objectives. Methodologically, their consideration can add information to our models and allow us to test previously unexplored theories. By considering multiple components of a single policy, scholars can leverage their similarities to gain both theoretical and empirical traction, while also allowing some of the richness of that policy to emerge within a parsimonious empirical model.

Yet the selection of an appropriate estimator for these models has been somewhat trickier. The studies cited above use a mélange of methods, including more advanced forms of EHA, event count methods, and linear regression. And while the preferred model will vary across applications given the structure of the data and the question(s) being asked, it seems appropriate to consider the various approaches at the hands of researchers. A variety of complications arise with these different methods, which I also discuss. In particular, the interrelatedness of these policy components may lead to violations of assumptions of independence both over time and across components. For example, future policy modifications may be contingent on the initial set of components adopted. Hopefully the process of systematically describing these models and discussing possible means of estimation will bring attention to these issues, reveal some alternate modeling strategies, and focus attention on recent theoretical and methodological advances in the study of state policy adoption.

2 Policies With Multiple Components

Focusing on the multiple components of a policy may allow researchers to develop richer models of the adoption and modification of that policy; in this section I provide some clarification of what I mean by a policy component and provide some examples to illustrate the discussion.

An important issue to address up front is whether it is best to view a set of components as parts of a single policy or whether they are, in fact, each separate policies. If the latter is true, then analysis can proceed as usual with the appropriate measure of each component studied separately. If not, then the researcher must make some decision about how to combine the information about a state's particular array of adopted components. The desire to do this will likely be a function of both the nature of the policy at hand and the researcher's question. For example, in most cases one would probably analyze state gaming policies separately: does a state have a lottery; does it allow commercial casino-style gaming; does it allow Indian gaming? While each of these are a part of state gaming policy, they are not necessarily alternate parts of a single policy decision. On the other hand, the decision about whether to negotiate agreements with Indian nations to allow parimutuel wagering, card games, games of chance or house-banked games may be seen as part of the same overall decision-making process. Even ignoring the possibility that there is some natural tendency for certain policy decisions to be viewed as components of a single policy rather than as distinct ones, it is clear that researchers are more frequently making this distinction.

Given the willingness to consider the different components of a single policy, what do those components look like? To put a little precision on the discussion, I introduce some notation. In a standard EHA the analysis focuses on explaining whether a state adopts a given policy. Let Y_{it} be an indicator variable for whether state i adopts policy Y in year t. In a standard EHA, states are included in the sample until they adopt the policy, after which they are excluded. This status is summarized by the risk set at time t: $i \in R(t)$ means that state i has not adopted the policy at time t and is therefore included in the analysis. In a repeated failures context, states are not precluded from experiencing future events and may remain in the risk set.

Now assume that the policy has multiple components; for now I will assume that those components are each dichotomous. In particular, assume that there are K distinct, binary components. The dependent variable and the risk set must be indexed by component, so let Y_{ikt} indicate whether state i adopts component k ($1 \leq k \leq K$) at time t and let $i \in R_k(t)$ indicate that state i is at risk of adopting that component at time t. Because these are distinct components, a state does not have to adopt all of them at the same time. In fact, a state can adopt none, all, or any combination of the K components in a given year. As with a standard EHA, one can allow for a single failure or repeated failures for each component.

Some of the features I have put on the components are restrictive and may not be realistic in a given policy area. For example, some of the components may not be dichotomous. Volden's (2006) six components of state Children's Health Insurance Program (CHIP) plans include some that he measures dichotomously, such as whether there is a monthly premium or a co-pay; others that are nominal, such as whether the plan is run under Medicaid, whether it is separate or whether it is a combination of the two; and some that are continuous, such as the maximum income for eligibility. Policies that involve such rich components will be even more difficult to analyze in any way save separately.

An additional concern is whether there is strong interdependence among some of the components. This could happen in two ways. Some of the components may be complementary in the sense that adopting one essentially guarantees or requires adopting the other. If this complementarity is strong enough, it may make sense to view them as a single component, especially if viewing them separately adds no more information than viewing them together. On the other hand, some of the components may be substitutes — they both accomplish the same goal, but implementing one makes the other superfluous. Finally, some of the components may be in opposition to each other, meaning that the implementation of two or more is mutually contradictory. For example, some states have passed laws protecting fast food retailers from obesity-related lawsuits while others have promoted awareness, treatment and physical fitness. In practice of course, few components will fall precisely into these extreme categories and may exhibit one or more of them to varying degrees. Further, it may be up to the researcher to determine whether components fall into these categories by definition or whether they appear to do so because of a specific pattern of implementation across states.

Lastly, there is the question of exactly how many components there are within a given policy. In some cases this falls naturally out of the theoretical question being asked, in others it may fall out of the structure of the policy in question. Yet often there will be a subjective part of its determination. One option is to rely on the decisions made by policymakers or policy experts when they consider the policy in question. Many research groups or advocacy groups explicitly break policies into multiple components when comparing them across states.

Certainly these various issues indicate the potential complexity of considering the components of a single policy. Yet they also reflect the potential richness of the policies that we have studied (and may help explain why others have not been studied) and have often treated as dichotomous. While it may be readily apparent when a state has adopted a lottery, it is harder to say exactly when it has adopted a pain-management policy: when it has one of the eight components? at least four of them? or all of them? Considering multiple components at one time may allow researchers to leverage the information provided by variation across states in how they adopt policies while also reflecting the underlying objective to arrive at a relatively concise explanation of policy in a given area.

3 Potential Modeling Strategies

In this section I discuss a number of ways that one could attempt to analyze the adoption of a policy with components of the nature described above. I consider three broad approaches to modeling the data, including using distinct models for each component, pooling the components into a single model, and treating the components as part of the same event structure rather than as distinct. Each of the methods has different strengths and weaknesses; some may be more appropriate for certain situations than others.

It is important to note that the method one chooses will depend on the particular question being asked as well. Different hypotheses may require different estimation strategies. For example, an analysis of the first adoption of a policy may wish to focus on the first year in which any component is adopted. A study intended to address how diffusion shapes policy modifications would likely want to look not just at when the first component is adopted, but also at which component is adopted and when additional components are added in the future. Further, the different approaches imply different interpretations of their results: a model of the time until first adoption should not be interpreted the same as a model which allows for repeated failures.

Consider the different questions one might wish to ask in the context of Indian gaming policy. First, one may wish to understand when states first negotiate gaming agreements with any tribes

— i.e., when does the state adopt Indian gaming (Boehmke 2005)? Second, one may wish to study how many tribes the state negotiates agreements with (Boehmke and Witmer 2004). Third, one could study the types of games allowed under those compacts. Fourth, one may wish to study the expansion of Indian gaming either by looking at expansion in the number of tribes with agreements or at expansion in the types of games or number of slots allowed under existing agreements. Each of these questions is valid and each potentially dictates a different empirical approach. In the rest of this section I review the relationship between these questions and various approaches researchers have employed.

3.1 Timing to Adoption

The first approach is to work within the EHA approach and modify the standard implementation to adapt to different questions. There are a variety of ways one can study the adoption process in this framework; I will focus on three general classes. The first consists of separate analysis of each component. The second involves pooling these analyses into one model that simultaneously estimates adoption of each component. Third, one may treat the components as identical and consider adoption of each as part of the same process.

In the first approach, one would merely estimate K separate EHA models — one for each component. Note that this does not necessarily rule out accounting for activity on the other components in each equation, however, as one can include variables measuring the status and characteristics of a state's activity on the other $K-1$ policy areas. This approach has the advantage of allowing full flexibility in modeling each component — one could conceivably enter completely different explanatory variables in each equation, for example. The trade-off is in the form of parsimony and ignoring the potential commonalities of the components of the policy in question.

In the second approach, the K EHA equations are pooled into a single equation (that is, the data for the K components are stacked and the parameters are estimated in a single model). At the extreme, one could assume that the coefficients are the same for each component and estimate a single one for each independent variable. This greatly increases parsimony by moving from $K \times M$ different parameter estimates (i.e., if there are the same $M - 1$ variables and a constant in each equation) to only M parameter estimates. Of course, one may expect or hypothesize that a given variable may have different effects on different components; this could be allowed for by creating interactions between variables and components. For example, do diffusion pressures operate on a component-by-component basis or do they act in concert?

The pooled analysis can be implemented by creating observations for each state in each year and for each policy component.[2] Thus the dependent variable is whether a state adopts that component in a given year. In a single-failure model, states will drop out of the risk set for a given component once they have adopted it, but they remain in the analysis if they have not yet adopted all K components. In a repeated failures context, they may remain in the risk set if additional adoptions are possible; one may wish to control for heterogeneity across event numbers.

There are a number of assumptions that one may wish to relax in this approach. Besides the possibility of allowing the coefficients for specific explanatory variables to be different for some components, one could allow the baseline hazard rates to vary across components. This would be relevant if some components are adopted at a slower rate than others. Allowing this additional form of flexibility is as simple as adding indicator variables for $K - 1$ of the components. Further, one can model various patterns of adoption over time. For example, states that have already

[2] In Stata, one can go from state-year observations with variables for each component to a data set with state-year-component observations using the `reshape` command.

adopted three components may be more likely to adopt the remaining components than states that have adopted none of them. This can be accounted for by including a running tally of the total number of components already adopted (various transformation can be performed to allow for possibly nonlinear effects).

Another advantage of pooling equations in this way is the ability to obtain better estimates of standard errors, though this could be mitigated when the effect of a given variable is different across components. In this case, one would merely arrive at the average effect, which could be a biased estimate of the effect on different components. This is one reason that one may wish to allow coefficients for a single covariate to be different for subsets of components.

While this approach is analogous to an elapsed time interpretation of the data (i.e., each state is at risk of each event from $t = 0$), the third EHA approach I discuss treats each component as part of the same process. That is, one can think of modeling activity within a policy area by studying whether a state adopts any component in a given year. This is analogous to a gap time model, which looks at the duration of time between each event. A special case of this approach is modeling the time until the first component is adopted: a state is in the risk set as long as none of the components is adopted and once at least one is adopted, it is dropped from the analysis (mathematically, $Y_{it} = \max_k \{Y_{ikt} : i \in R_k(t)\ \forall k\}$). Essentially, one is estimating the effects on timing until first activity. A more general approach uses a repeated failures interpretation — this focuses on whether a state adopts any components in a given year and keeps states in the risk set until they have adopted all components. Thus the dependent variable is $Y_{it} = \max_k \{Y_{ikt} : i \in R_k(t)\ \exists k\}$ and states are excluded only if they have adopted all K components; states need not be excluded if a repeated events framework is adopted.

This approach ignores the uniqueness of each component and makes it difficult to include component-specific variables or coefficients. Yet is has at least one advantage relative to a standard EHA, in that it retains states in the analysis after initial adoption and until they have adopted all components. This makes it possible to study policy adoption and modification with one model. It also allows one to adapt all of the methods developed for repeated failure models. For example, one may wish to allow for different baseline hazards for the first, second, third events, etc. This is accomplished by adding in indicators for the number of previous failures. Alternatively, one could simply add a variable counting the number of previous failures. One could also add additional covariates for different failure numbers, potentially allowing the effect of interstate diffusion to vary for initial adoption and subsequent expansions.

Each of these approaches allows one to draw on the considerable strengths of EHA, including dealing with common issues like right-censoring and duration dependence (see Beck, Katz and Tucker 1998). They can each be performed using any variety of EHA models, including discrete ones like logit or probit, or continuous ones like the Weibull and Cox models[3]

These approaches also raise important concerns about independence, especially when adoption of other components is included in the model. If the unobserved factors that influence the adoption of each component are correlated, then including adoption of other components may result in biased estimates of their interrelated effects. Of course, if there is an exogenous dependence between events, then omitting them can also introduce bias. Because one is estimating a model for binary outcomes and because states exit the risk set for different components at different times, it may be difficult to analyze patterns of correlations in the error terms across components.

[3]See Branton and Jones (2005) for a discussion of the use of continuous-time duration models for studying state policy adoptions. I do not discuss these estimators in this paper, but all of the discrete EHA models I estimate could just as easily be estimated using a continuous-time approach.

3.2 Number of Components Adopted

One common feature of all the previous methods is that they each model a dichotomous outcome. The pooled elapsed-time approach is the only one that allows multiple failures to occur in the same year. The repeated events approach only analyzes whether at least one component is adopted in a given year, but ignores information about the number of events adopted that year. This information can be valuable, especially if adoption of multiple components in the same year is fairly common.

One way to incorporate this information is to model the number of components adopted in each year. Thus one would analyze $Y_{it} = \sum_k Y_{ikt}$ for $i \in R_k(t)$.[4] The dependent variable therefore changes from dichotomous to ordinal, and different methods are required. Two common ways to model such dependent variables are using linear regression and event count models. For a variety of reasons, event count models such as Poisson regression and the negative binomial model are preferred in such cases, particularly when the counts tend to be small (see, e.g., King (1989a); King (1989b); Maddala (1983); or Cameron and Trivedi (1998) for more information on event count models). In the analysis of state policy adoption one would almost certainly prefer the negative binomial to the Poisson model since the latter assumes that the rate of occurrence of events is constant within time periods (years, in this case). Since states that adopt multiple components in the same year are likely to do so at the same time, this assumption probably does not hold.

One issue that arises here in the single-event framework is how to deal with states that have adopted some components but not all of them. Since I have assumed that states can only adopt each component once, the count of components that can adopted in a given year is limited by the

[4]In some applications states may enact multiple pieces of legislation for same component in a single year. This would require a simple extension of this notation to allow Y_{ikt} to be integer-valued.

number that have not yet been adopted. This maximum possible count is referred to as exposure and can be accounted for by including the log of the number of unadopted components as an independent variable (if the coefficient is restricted to be one, this is equivalent to estimating the proportion of remaining components adopted in a given year).[5] In a repeated events context, one may include tallies or indicators for the number of events that have already occured.

4 Comparison of Different Models

In this section I compare the results obtained from estimating many of the estimators discussed in the previous section. It is important to remember that the different models correspond to different questions, so one should not expect *à priori* that the results will be the same across estimators. The similarity will also vary with the effect of each included variable across components: if a variable has a positive effect on one component and a negative effect on the second, then pooling components may indicate no effect. This means that the comparison of results will vary across policies depending on the process for each of the individual components. For the comparison in this paper I use data from state obesity policy, which is discussed in the following section.

4.1 State Obesity Legislation Adoptions

The continuing increase in American's weight has lead many researchers to declare an obesity epidemic that increasingly poses grave risks for citizens' health and the nation's health care system. Studies estimate that about one third of Americans are overweight (i.e., with a body mass index

[5]See King (1989b) or Maddala (1983) for more information on including the logarithm of exposure as an independent variable.

between 25 and 30) and another third are obese (BMI of at least 30 – see Flegal, Carroll, Ogden, and Johnson (2002) for definitions and these estimates). These numbers are on the rise, from 14% obese in 1978 and 22.5% in 1990 (Mokdad, Serdula, Dietz, Bowman, Marks, and Koplan 1999); every state saw an increase in obesity rates from 1990 to 1999, with an average increase of 40% (Mokdad et al.1999). These trends exist across the board, including among children, of which 15% are overweight and 30% are at risk of being overweight (Ogden, Flegal, Carroll, and Johnson 2002) and exhibit many of the same consequences of these statuses.[6]

These trends, along with the individual and social costs that obesity carries, explain the reference to an obesity epidemic by many health researchers and public officials. Excess weight has been found to be associated with a variety of health problems, including cardiovascular disease, Type 2 diabetes, hypertension, stroke, etc. (Must, Spadano, Coakley, Field, Colditz, and Dietz 1999). Studies suggest that the costs of obesity-related conditions account for 7-10% of health care costs in the U.S. (Mokdad et al. 1999; and Morone 2005). Further, estimates indicate that anywhere from 112,000 (Flegal, Graubard, Williamson, and Gail 2005) to 220,000 deaths (Allison, Fontaine, Mansen, Stevens, and VanItallie 1999) were attributable to obesity at the turn of the last century. Put another way, individuals with a BMI over 30 have, on average, a life expectancy reduction of two to five years.[7]

During this period, there was a dramatic increase in attention to the problem by the public, media and lawmakers.[8] Media coverage itself expanded from sixty-two articles in 1980 to 6500

[6]For children, overweight corresponds to being above the ninety-fifth percentile whereas at-risk of being overweight corresponds to being between that and the eighty-fifth percentile.

[7]It is worth noting that most studies find a net health increase among those in the overweight category (Campos, Saguy, Ernsberger, Oliver, and Gaesser 2006; Flegal et al. 2005). In general, the effects of BMI are U-shaped, with both overweight and underweight (i.e., BMI below 17.5) individuals experiencing greater morbidity and mortality rates. Further, some question whether the effects of obesity are causal or merely cosymptomatic of some underlying condition (e.g., Campos et al. 2006).

[8]Public health researchers had long recognized the trend in weight gain in the United States as indicated by Bres-

in 2004 in U.S. News Sources; these reports also tend to exaggerate the extent of the problem (Campos et al. 2006) and focus their reporting on dramatic interpretations of the situation (Saguy and Almeling 2007). Lawmakers, too, have been caught up in the flurry of interest, but with no action at the Federal level by 2004, advocates have been forced to rely on the courts or to press state or local officials (Kersh and Morone 2005).

Here, I focus on efforts by state lawmakers to address the obesity issue by studying legislation passed in the fifty states between 1998 and 2005. States have attempted to address (or to appear to have addressed) the issue in a variety of ways. For example, many states have banned the sale of sugary drinks during certain school hours; others have increased physical education requirements; still others have passed legislation requiring insurers to cover certain types of treatments for obesity (including gastric bypass surgery). At the same time, other states have responded by passing so-called "cheeseburger bills" that protect the fast food industry from consumer lawsuits. Thus there has been a wide range of legislative activity in the states over the past decade to address obesity, with some legislatures seeking to aid the public and others protecting producers from litigation.

To obtain a more complete picture of state activity on this issue, I gathered data from a number of sources.[9] From 1998 until 2005, a total of 313 pieces of legislation were enacted across the fifty states. Almost three-quarters of these were passed since 2003; only ten laws were passed between 1998 and 2000 (and we found none in 1997).

After reading through the summaries of these bills we coded them based on the different issues

low's 1952 address highlighting the trends and negative consequences (Breslow 1952).

[9]These included reports and databases from the National Conference of State Legislatures, reports sponsored by the Robert Wood Johnson Foundation and put together by Health Policy Tracking Service, and two databases available through the Center for Disease Control: State Obesity-Related Legislation and Nutrition and Physical Activity. Legislation was cross-checked and in some cases compared to the listings available from state legislature's websites.

that they addressed and then coded these different issues into eleven primary components:

1. Awareness: promote awareness of obesity as an issue and ways to deal with it. May create health awareness days, weeks, etc.; government advertising campaigns; promote BMI measurement; creating BMI report cards for students.
2. Committee/Research: create or continue a government commission, committee or task force, either at the state or local level, to study or create policy solutions.
3. Health Education: promote or require health education in schools.
4. Insurance: address coverage for obesity-related treatment or for treatment of related problems. Includes private and Medicaid coverage.
5. Labeling: restaurant food nutrition labeling.
6. Liability: provide immunity from liability for food retailers relating to individuals' consumption-related weight gain or associated conditions.
7. Medical Treatment: restrict or permit medical treatments for obesity.
8. Nutrition/Wellness: promote public nutrition, fitness and wellness. Includes nutritious grocers acts and farm to market acts.
9. Physical Education: relating to physical education requirements in schools or school athletic programs.
10. School Nutrition: promote nutritious meals in schools, school meal programs, vending machine restrictions, contracts with food and beverage vendors, farm to school policies, and school/community gardens.
11. Transportation: improve infrastructure for walking/jogging/cycling, safe routes to school acts, promote or facilitate personal locomotion.

[Table 1 Here.]

Table 1 shows the trends in adoptions across these different component areas. Note that since bills may address multiple areas at once, there are more components adopted than there are bills enacted. Further, states may pass more than one piece of legislation in each area, which explains how some components are adopted more than fifty times. The four areas with the most activity are Committee/Research (76 times), Physical Education (67), Awareness (65), and School Nutrition (59); at the other end of the spectrum are Insurance (11) and Labeling (3). The top four areas are addressed in about thirty states each, implying about two pieces of legislation over the eight year period examined. These data are used to construct various models to explain state obesity policy and to illustrate many of the issues discussed in the previous section.

4.2 Control Variables

The models contain a number of variables intended to explain state-level adoptions of obesity legislation components, most of which are common in the state policy adoption and diffusion literature. Political variables include state-level ideology (Erikson, Wright and McIver 1993), divided government, unified Republican government, and legislative professionalism in 1990 (King 2000). Measures of innovativeness include total state population and real income per capita.[10] Finally, diffusion pressures are measured with the number of component adoptions in contiguous states or, alternatively, the number of components adopted in those states (see, e.g., Berry and Berry 1990). Finally, I include additional variables to help measure the demand for public policy solutions to the obesity epidemic by calculating the percentage of a state's population that is overweight or obese.[11] The results presented are not intended to be definitive explanations of obesity legislation adoption, but are used to facilitate model comparison. That said, the results tend to be fairly robust to the inclusion of other variables.

[10] These variables are culled from the U.S. Census and the Statistical Abstract of the States, various years.

[11] These two variables are constructed according the definitions mentioned previously and are calculated using data from the Behavioral Risk Factor Surveillance System's 1998-2005 studies.

4.3 Analyzed Separately

The first analysis I present compares separate EHA analyses of the adoption of ten components (Labeling did not have enough activity to generate meaningful statistical results – it is therefore not analyzed on its own). This approach ignores any commonality or cross-component influences and is equivalent to estimating ten separate event history models. This approach may be useful in the context of obesity legislation since some laws protect consumers while others protect the fast food industry; further, some of the laws are perhaps mere grandstanding (e.g., "Walking Wednesday," which encourages parents and children to walk to school together) while others have very specific policy bite. For the diffusion variable I measure the number of contiguous neighbors that have adopted the same provision before the current year. These results are presented in Table 2. Two variations on this model are run: the first considers time until first adoption (removing states that have adopted from the risk set) whereas the second approach allows for repeated failures. In the second approach I include a indicator for whether each state has previously passed legislation for the component in question in order to test whether states that have already acted in a given area are more or less likely to act again. For comparison, I also include a pooled analysis that combines the ten separate analyses and assumes constant effects across them.

[Table 2 Here.]

The time until first failure results are presented in Table 2 while the repeated failures results are in Table 3. Overall, the results indicate a some consistency across components in the factors that influence adoption, though more coefficients emerge as statistically significant in the repeated failures analysis. For example, states with unified republican governments are consistently less likely to adopt any of the provisions, with significant coefficients for five of the ten areas; larger states tend to be significantly more likely to adopt each component as well. On the other hand, some differences do emerge. For example, percent overweight has a positive effect on Awareness legislation but a negative effect on Liability legislation; Liberal Ideology has a positive effect on health education legislation but a negative effect on transportation and infrastructure legislation. This serves to highlight the fact that adoption of policy components may be driven by different factors. Further, note that there is little evidence of event dependence, in the sense that states that have already adopted a component are not significantly more or less likely to pass more legislation on that issue (the one exception is nutrition legislation).

[Table 3 Here.]

4.4 Pooled Analyses

In this section I consider variations on models that pool the analysis into a single model (i.e., observations are at the state-year-component level). At one extreme, this is akin to assuming that the coefficients for each of the eleven issues areas are the same across the separate models. Yet this assumption can be relaxed in a number of ways, some of which I highlight here. First, I include fixed effects for each component. This allows the baseline rate of adoption to vary across components, which seems likely given that some components are adopted by most states while others, such as restaurant labeling, are only adopted by a handful. Second, I also include indicator variables for whether a state has adopted each of the other provisions to control for ordering effects.[12]

The first five models that I present are event history analyses of the timing until first adoption

[12] This is accomplished by creating eleven indicator variables for whether a state has previously adopted each component and then including them as regressors. In the repeated events approach, I set the value of the variable to zero for observations corresponding to the same component since I already have a variable for the presence of the current component.

or of repeated adoptions; the final model is a Poisson model of the number of events for each component (estimation of a negative binomial model did not reject the Poisson model's assumption of equidispersion).[13] In the event history models I compare results when component fixed effects are included to allow for different baseline hazard rates, while the repeated failures model also includes a specification that includes fixed effects for whether each of the other components was previously adopted, which addresses whether states that have adopted, for example, liability laws are less likely to adopt other components.

[Table 4 Here.]

The results for these more parsimonious models are presented in Table 4. These results show more consistency in the effects of the various independent variables. The percentage of a state's population that is overweight has a positive and significant effect on adoption (whether first or repeated) in all five of the event history models. Both unified republican government and divided government have negative and significant effects in all six models, while total population is always positive and significant.

The results also demonstrate the importance of controlling for various forms of heterogeneity. First, in all of the models with fixed effects, a χ^2 test strongly rejects the null hypothesis that they should be excluded. While these coefficients are not shown, the results for the component fixed effects indicate that compared to the baseline category of awareness legislation, all of the other categories have significantly lower baseline hazard rates, with the exceptions of creating committees, physical education and school nutrition, which are generally negative though not significant. The results for lagged component adoption indicate the adoption of labeling laws significantly de-

[13]These models are straightforward to estimate in most programs. Instead of each observation representing a state-year, I created a data set with state-year-component observations. The pooled model is estimated with a single probit command; the separate event models are estimated by restricting the analysis by provision.

creases while nutrition laws significantly increase future adoptions of other components. Second, the repeated events models indicate that when a state has already adopted a provision, it is significantly more likely to pass additional legislation on that provision as well. Third, the inclusion of the fixed effects models influence the conclusions drawn about other variables. For example, the neighbors' adoption variable produces positive and significant coefficients whenever provision fixed effects are not included.

4.5 Combined Analysis for Same Event

In this section I present results from models that treat the different components as identical events. That is, the unit of analysis shifts to the state-year level and the adoption of any component is considered as an obesity legislation event. In the event history models, the dependent variable is coded as a one in any year in which a state adopts at least one component. In the negative binomial and OLS models for the number of events, the dependent variable is the number of components adopted. In the obesity legislation case, about two-thirds of the observations with at least one event have more than one component adopted. This suggests that a substantial amount of information may be lost when this count is reduced to an indicator.[14]

[Table 5 Here.]

These results are presented in Table 5. Some similar results emerge: percent overweight and total population tend to increase adoption while unified republican governments are less likely to adopt. Ideology is found to increase the time until the first event, while divided government decreases the number of events but is not significant in the event history models. Previous adoption

[14]The number of events ranges from zero to seventeen, with a mean of one. There are 147 cases out of 400 with a positive number of events, and the conditional mean number of events is 2.75.

of obesity legislation is also only significant in the models for the number of events. Finally, unlike in some of the pooled analyses, neighbors' adoptions do not appear to matter.

5 Discussion

This paper has discussed various models available for studying the adoption of policies with multiple components. While there are potential theoretical and statistical advantages to considering multiple components, there are also methodological ambiguities in how best to model these data. I have attempted to review some of the methods available and to discuss the different questions they address, some of their strengths and weaknesses, and new methodological issues that arise in the study of multiple components.

Given that the conclusions from the different models are difficult to compare since they may estimate different processes (e.g., time until adoption of any component versus time until adoption of a specific component), it is impossible to say which model is best in just about any sense of that word. The choice will depend not just on the question being asked, but also on how various factors influence the adoption of each component. First, if the effects of a variable are different across components, in particular if it has both positive and negative effects, then the various approaches that pool or combine the data will tend to under report their importance. Second, because the same event approaches don't respect the uniqueness of each component, they make it impossible to account for the heterogeneity of influences, providing at best some sort of (weighted) average effect. So while they may provide additional information, it is probably most valuable when components are more similar than not. The best approach will likely involve conducting separate analyses and then determining which variables/components can be pooled together and which might require separate models or variables.

The pooled analysis is much more flexible since it allows for the specification of different relationships across components. That is, one can interact an independent variable with a given component(s) to allow its coefficient to vary. Yet at the same time one can still gain information by leveraging the similarity of influences across components. Further, it is easy to tell when the homogeneity assumption is potentially violated by just estimating separate models for each component or performing test for less restrictive models (i.e., whether to include component fixed effects).

In order to illustrate these different approaches, I estimated various models to explain state adoption of eleven different categories of obesity-related legislation. The results were generally consistent across models, but a number of differences did emerge. For example, unified republican and divided government were both found to significantly decrease the adoption of obesity legislation across a variety of specifications. On the other hand, the influence of neighboring states' adoptions was found to depend on the specification used. In addition, the effect of some variables appeared to vary across categories of legislation: the percentage of a state's population categorized as overweight tended to increase the chance of adoption of most components, but decreased the probability of adopting limited liability legislation. Given the different motivations behind the latter it is not surprising that some differences were found.

While the substantive example used in this exploration is amenable to the assumptions made about the dichotomous nature of policy components, it is clear from research in this area that many components do not fit this assumption. This raises the question of how to generalize the current models to allow for ordinal and (perhaps with more difficulty) nominal components. Taking this step would throw the event adoption structure out the window since states could "adopt" a component that is monetary, but would then likely fiddle around with the exact amount from year to year. Further, this could make the pooling and count approaches more difficult. Though at the same time, allowing for changes after initial adoption would reduce the problem of controlling for the number of unadopted components.

Considering these alternate component structures may lead one to a more general solution. For example, one could consider constructing some sort of policy index that takes a linear combination of a state's values for the different components. In fact, this approach has already been taken in some cases. Scholars have constructed two indices to measure state TANF policy (e.g., Yu 2005) and Jacoby and Schneider (2001) use a spatial proximity model to develop a single measure that captures state spending priorities across fifteen different issue areas. Perhaps these or similar approaches could be adapted to the case discussed here, with dichotomous components that are not repealed.

References

Allison, Paul D. 1984. *Event History Analysis: Regression for Longitudinal Event Data.* Sage University Paper Series on Quantitative Applications in the Social Sciences, series no. 07-046. Beverly Hills and London: Sage Publications.

Allison, David B., Kevin R. Fontaine, JoAnn E. Mansen, June Stevens, and Theodore VanItallie. 1999. "Annual Deaths Attributable to Obesity in the United States." *Journal of the American Medical Association* 282(16): 1530-1538.

Beck, Nathaniel, Jonathan N. and Richard Tucker. 1998. "Taking Time Seriously: Time-Series-Cross-Section Analysis with a Binary Dependent Variable." *American Journal of Political Science* 42(4): 1260-1288.

Berry, Frances Stokes, and William D. Berry. 1990. "State Lottery Adoptions as Policy Innovations: An Event History Analysis." *American Political Science Review* 84: 395-415.

Berry, William, and Brady Baybeck. 2005. "Using Geographic Information Systems to Study Interstate Competition." *American Political Science Review* 99: 505-19.

Boehmke, Frederick J. 2005. *The Indirect Effect of Direct Legislation: How Institutions Shape Interest Groups Systems.* Columbus: Ohio State University Press.

Boehmke, Frederick J. and Richard Witmer. 2004. "Disentangling Diffusion: The Effects of Social Learning and Economic Competition on State Policy Innovation and Expansion." *Political Research Quarterly* 57: 39-51.

Box-Steffensmeier, Janet M. and Bradford D. Jones. 1997. "Time Is of the Essence: Event History Models in Political Science." *American Journal of Political Science* 41: 1414-1461.

Box-Steffensmeier, Janet M. and Bradford D. Jones. 2004. Event History Modeling: A Guide for Social Sciences. Cambridge: Cambridge University Press.

Breslow, Lester. 1952. "Public health aspects of weight control." *American Journal of Public Health* 42(9): 1116-20. Reprinted in (2006) *International Journal of Epidemiology* 35: 10-12.

Cameron, A. Colin and Pravin K. Trivedi. 1998. *Regression Analysis of Count Data.* Cambridge: Cambridge University Press.

Campos, Paul, Abigail Saguy, Paul Ernsberger, Eric Oliver, and Glen Gaesser. 2006. "The Epidemiology of Overweight and Obesity: Public Health Crisis or Moral Panic?" *International Journal of Epidemiology* 35(1): 55-60.

Council of State Governments. Various years. *The Book of the States.* Lexington: Council of State Governments.

Erikson, Robert S., Gerald C. Wright, and John P. McIver. 1993. *Statehouse Democracy: Public Opinion and Policy in the American States*. Cambridge: Cambridge University Press.

Dubin, Jeffrey A. and Douglas Rivers. 1990. "Selection Bias in Linear Regression, Logit and Probit Models." *Sociological Methods and Research* 18:354-365.

Flegal, Katherine M., Barry I. Graubard, David F. Williamson, and Mitchell H. Gail. 2005. "Excess Deaths Associated With Underweight, Overweight, and Obesity." *Journal of the American Medical Association* 293(15): 1861-7.

Flegal, Katherine M., Margaret D. Carroll, Cynthia L. Ogden, and Clifford L. Johnson. 2002. "Prevalence and Trends in Obesity Among US Adults, 1999-2000." *Journal of the American Medical Association* 288(14): 1723-27.

Imhof, Sara. 2006. *Promoting a "Good Death": An Investigation of the Determinants that Explain State Medical Board Adoptions of Pain Management-Enhancing Policies in the United States.* Ph.D. dissertation, University of Iowa.

Jacoby, William G.; Saundra K. Schneider. 2001. "Variability in State Policy Priorities: An Empirical Analysis." *The Journal of Politics* 63(2): 544-568.

Jones, Bradford S. and Regina P. Branton. 2005. "Beyond Logit and Probit: Cox Duration Models for State Policy Adoption." *State Politics and Policy Quarterly* 5(4): 420-443.

Kersh, Rogan and James A. Morone. 2005. "Obesity, Courts, and the New Politics of Public Health." *Journal of Health Politics, Policy and Law* 30(5): 839-868.

King, Gary. 1989a. "Statistical Models for Political Science Event Counts: Bias in Conventional Procedures and Evidence for The Exponential Poisson Regression Model." *American Journal of Political Science* 32: 838-863.

King, Gary. 1989b. "Variance Specification in Event Count Models: From Restrictive Assumptions to a Generalized Estimator." *American Journal of Political Science* 33: 762-784.

King, James D. 2000. "Changes in Professionalism in U.S. State Legislatures." *Legislative Studies Quarterly* 25(2): 327-343.

Maddala, G.G. 1983. *Limited Dependent and Qualitative Variables in Econometrics.* Cambridge: Cambridge University Press.

Mokdad, Ali H., Mary K. Serdula, William H. Dietz, Barbara A. Bowman, James S. Marks, and Jeffrey P. Koplan. 1999. "The Spread of the Obesity Epidemic in the United States, 1991-1998." *Journal of the American Medical Association* 282(16): 1519-22.

Must, Aviva; Jennifer Spadano; Eugenie H. Coakley; Alison E. Field; Graham Colditz; and William H. Dietz. 1999. "The Disease Burden Associated With Overweight and Obesity." *Journal of the American Medical Association* 282(16): 1523-29.

Ogden, Cynthia L.; Katherine M. Flegal; Margaret D. Carroll; and Clifford L. Johnson. 2002. "Prevalence and Trends in Overweight Among US Children and Adolescents, 1999-2000." *Journal of the American Medical Association* 288(14): 1728-1732.

Saguy, Abigail C. and Rene Almeling. 2007. "Fat in the Fire? Science, the News Media, and the 'Obesity Epidemic'." Working paper, Robert Wood Johnson Scholar in Health Policy Research Program (WP-34).

Shipan, Charles R., and Craig Volden. 2006. "Bottom-Up Federalism: The Diffusion of Antismoking Policies from U.S. Cities to States." *American Journal of Political Science* 50(4): 825-843.

Shipan, Charles R., and Craig Volden. 2007. "Local Antismoking Laws and the Mechanisms of Policy Diffusion." Working paper.

U.S. Bureau of the Census. Various years. *Statistical Abstract of the United States.* Washington: US Government Printing Office.

Volden, Craig. 2006. "States as Policy Laboratories: Emulating Success in the Children's Health Insurance Program." *American Journal of Political Science* 50: 294-312.

Walker, Jack L. 1969. "The Diffusion of Innovations among the American States." *American Political Science Review* 63: 880-899.

Yackee, Susan Webb. 2005. "Coalitions in Conflict: Competing Interests in State Medical Malpractice Laws." Paper Presented at the State Politics and Policy Conference.

Yu, Eric C. H. 2005. "The Impact of Welfare Reforms on Welfare Caseload." Paper Presented at the State Politics and Policy Conference.

Table 1: Adoption of Obesity Legislation Components by Year

	1998	1999	2000	2001	2002	2003	2004	2005	Total	# States
Awareness	1	2	0	4	8	20	14	16	65	29
Committee/Research	1	2	2	16	4	26	12	13	76	31
Health Education	0	0	0	0	0	7	6	16	29	18
Insurance	0	1	0	1	1	2	2	4	11	9
Labeling	0	0	0	0	0	1	1	1	3	3
Liability	0	0	0	0	0	2	14	8	24	22
Medical Treatment	0	0	2	1	0	4	3	8	18	11
Nutrition/Wellness	0	0	0	2	2	5	8	11	28	13
Physical Education	0	0	1	4	5	14	16	27	67	31
School Nutrition	0	0	0	2	8	14	10	25	59	32
Transportation	0	0	0	4	2	3	9	7	25	16
Total	2	5	5	34	30	98	95	136	405	215

Source: author's data, compiled from various sources. See text for more information.

Table 2: Probit Event History Analyses of First Policy Adoption, by Component

	Pooled	Aware.	Comm.	Health Ed.	Insur.	Liab.	Treat.	Nutr.	P.E.	Sch. Nutr.	Transp.
% Overweight BMI	1.953**	6.227	3.004	10.466	3.401	−22.816**	−2.851	1.460	1.215	3.163	2.842
	(0.889)	(4.300)	(3.538)	(13.329)	(4.267)	(11.632)	(4.121)	(3.419)	(3.070)	(3.050)	(4.662)
% Obese BMI	−1.761	0.204	−3.246	2.834	−0.169	−9.649	1.735	1.089	−3.145	−2.763	−2.075
	(1.551)	(4.948)	(5.555)	(7.715)	(7.981)	(7.255)	(8.096)	(6.346)	(4.813)	(5.415)	(7.698)
Liberal Ideology	−0.006	−0.018	−0.034	−0.063*	−0.043	−0.034	−0.032	0.039	−0.008	0.035*	0.119**
	(0.009)	(0.024)	(0.025)	(0.034)	(0.029)	(0.028)	(0.026)	(0.025)	(0.018)	(0.020)	(0.038)
Unified Republican Government	−0.521**	−0.780*	−1.977**	−0.683	0.185	0.454	−0.158	−0.822	−0.705*	−0.823**	−1.099*
	(0.162)	(0.471)	(0.450)	(0.497)	(0.522)	(0.565)	(0.483)	(0.599)	(0.376)	(0.368)	(0.569)
Divided Government	−0.246**	−0.393	−0.722**	−0.089	−0.005	0.233	0.087	−0.131	0.023	−0.539*	−1.304**
	(0.115)	(0.341)	(0.265)	(0.381)	(0.504)	(0.491)	(0.334)	(0.378)	(0.286)	(0.302)	(0.356)
Total Population	0.038**	0.039	0.037	0.069	0.004	0.049	0.037*	0.026	0.093**	0.069**	0.091*
	(0.008)	(0.027)	(0.023)	(0.043)	(0.033)	(0.031)	(0.021)	(0.041)	(0.031)	(0.029)	(0.050)
Personal Income	−0.008	−0.027	−0.049	0.024	0.065	−0.017	−0.007	−0.041	−0.039	−0.013	0.003
	(0.014)	(0.038)	(0.040)	(0.052)	(0.042)	(0.046)	(0.045)	(0.043)	(0.041)	(0.047)	(0.044)
Legislative Professionalism	−0.672*	0.634	1.223	−0.391	0.666	−2.574	0.424	−1.109	−3.288**	−2.676**	−2.312
	(0.385)	(1.190)	(1.164)	(1.641)	(1.326)	(1.804)	(1.114)	(1.950)	(1.374)	(1.079)	(2.108)
Neighbors' Adoptions	0.217**	0.062	0.134*	0.073	0.214	0.116	−0.443	0.211	−0.010	0.153	−1.348**
	(0.036)	(0.110)	(0.080)	(0.232)	(0.381)	(0.230)	(0.455)	(0.233)	(0.134)	(0.105)	(0.416)
Time	0.326**	0.448*	0.473*	2.557**	−0.037	11.177**	0.205	0.492*	0.702**	0.621**	1.090*
	(0.116)	(0.239)	(0.242)	(1.273)	(0.209)	(4.641)	(0.272)	(0.286)	(0.291)	(0.285)	(0.602)
Time Squared	−0.014	−0.036	−0.032	−0.179	0.021	−0.864**	0.016	−0.033	−0.028	−0.027	−0.047
	(0.012)	(0.029)	(0.029)	(0.115)	(0.029)	(0.383)	(0.035)	(0.035)	(0.033)	(0.032)	(0.062)
Constant	−2.736**	−4.083**	−1.666	−16.230**	−6.334**	−25.905*	−3.212*	−1.954	−2.108*	−2.449	−3.479*
	(0.471)	(1.941)	(1.485)	(7.711)	(1.497)	(14.349)	(1.737)	(1.472)	(1.235)	(1.524)	(1.991)
Observations	3873	313	302	370	368	369	369	364	337	341	359

Notes: ** indicates $p \leq .05$; * $p \leq .10$. Standard errors calculated by clustering on state.

Table 3: Probit Event History Analyses of Repeated Policy Adoptions, by Component

	Pooled	Aware.	Comm.	Health Ed.	Insur.	Liab.	Treat.	Nutr.	P.E.	Sch. Nutr.	Transp.
% Overweight BMI	2.314**	6.468**	2.028	9.809	1.258	−22.816**	−2.993	−0.000	1.675	3.383	0.246
	(0.809)	(2.348)	(2.871)	(13.061)	(4.285)	(11.632)	(3.441)	(3.152)	(2.244)	(2.308)	(3.061)
% Obese BMI	−2.370	−2.720	−1.154	−3.300	2.718	−9.649	1.849	2.669	−4.252	−4.200	2.685
	(1.446)	(3.749)	(4.246)	(6.665)	(8.345)	(7.255)	(6.649)	(5.795)	(3.690)	(4.011)	(4.733)
Liberal Ideology	−0.003	−0.006	−0.017	−0.039	−0.036	−0.034	−0.034	0.040*	−0.018	0.024	0.090**
	(0.007)	(0.016)	(0.021)	(0.033)	(0.025)	(0.028)	(0.025)	(0.023)	(0.016)	(0.017)	(0.032)
Unified Republican Government	−0.549**	−0.812**	−1.372**	−0.533	0.288	0.454	−0.387	−0.914*	−0.691*	−0.787**	−0.449
	(0.146)	(0.389)	(0.332)	(0.457)	(0.451)	(0.565)	(0.377)	(0.526)	(0.381)	(0.350)	(0.462)
Divided Government	−0.216**	−0.359	−0.284	−0.035	0.080	0.233	−0.070	−0.390	0.001	−0.347	−0.950**
	(0.107)	(0.250)	(0.176)	(0.389)	(0.439)	(0.491)	(0.241)	(0.282)	(0.310)	(0.294)	(0.257)
Total Population	0.040**	0.051**	0.050**	0.057	−0.006	0.049	0.040**	0.021	0.093**	0.050**	0.050
	(0.009)	(0.022)	(0.018)	(0.035)	(0.031)	(0.031)	(0.017)	(0.034)	(0.022)	(0.023)	(0.040)
Personal Income	−0.011	−0.048	−0.038	−0.008	0.079*	−0.017	0.007	−0.026	−0.019	−0.033	0.021
	(0.013)	(0.030)	(0.031)	(0.043)	(0.043)	(0.046)	(0.051)	(0.036)	(0.035)	(0.029)	(0.030)
Legislative Professionalism	−0.658	0.685	0.262	−0.492	0.743	−2.574	0.281	−1.002	−3.054**	−1.413	−2.031
	(0.404)	(0.843)	(0.837)	(1.454)	(1.216)	(1.804)	(0.991)	(1.464)	(0.967)	(0.900)	(1.617)
Neighbors' Adoptions	0.165**	0.021	0.070	−0.057	0.290	0.116	−0.330	0.021	0.002	0.102	−0.821**
	(0.034)	(0.097)	(0.081)	(0.235)	(0.316)	(0.230)	(0.432)	(0.217)	(0.111)	(0.091)	(0.360)
Time	0.378**	0.497**	0.448**	1.998**	−0.038	11.177**	0.173	0.509	0.648**	0.590**	0.819**
	(0.095)	(0.252)	(0.185)	(0.965)	(0.215)	(4.641)	(0.288)	(0.321)	(0.285)	(0.281)	(0.410)
Time Squared	0.357**	−0.034	−0.034	−0.125	0.016	−0.864**	0.019	−0.033	−0.020	−0.019	−0.044
	(0.122)	(0.029)	(0.023)	(0.091)	(0.029)	(0.383)	(0.035)	(0.035)	(0.032)	(0.030)	(0.047)
Has this Provision	−0.017	0.017	0.018	−0.014	−0.044		0.268	0.790**	0.063	−0.176	−0.118
	(0.013)	(0.238)	(0.225)	(0.492)	(0.485)		(0.382)	(0.291)	(0.266)	(0.259)	(0.615)
Constant	−2.680**	−3.053**	−1.834	−11.773*	−6.439**	−25.905*	−3.465*	−2.031	−2.751**	−2.094**	−3.490**
	(0.449)	(1.155)	(1.205)	(6.201)	(1.360)	(14.349)	(1.901)	(1.307)	(1.153)	(1.024)	(1.242)
Observations	3873					384					

Notes: ** indicates $p \leq .05$; * $p \leq .10$. Standard errors calculated by clustering on state.

Table 4: Pooled Analyses of Obesity Legislation Adoptions

	Event History					Poisson
	First Event		Repeated Events			
% Overweight BMI	1.953**	1.864*	2.314**	1.991**	2.635 **	2.133
	(0.889)	(1.029)	(0.809)	(0.915)	(0.880)	(1.922)
% Obese BMI	−1.761	−1.629	−2.370	−1.808	−3.022*	−0.384
	(1.551)	(1.841)	(1.446)	(1.662)	(1.597)	(3.385)
Liberal Ideology	−0.006	−0.007	−0.003	−0.004	−0.004	−0.016
	(0.009)	(0.010)	(0.007)	(0.009)	(0.009)	(0.015)
Unified Republican Gov't	−0.521**	−0.618**	−0.549**	−0.612**	−0.545 **	−1.183**
	(0.162)	(0.178)	(0.146)	(0.159)	(0.159)	(0.281)
Divided Government	−0.246**	−0.273**	−0.216**	−0.226**	−0.185*	−0.501**
	(0.115)	(0.118)	(0.107)	(0.109)	(0.108)	(0.222)
Total Population	0.038**	0.046**	0.040**	0.047**	0.040 **	0.072**
	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.015)
Personal Income	−0.008	−0.014	−0.011	−0.014	−0.014	−0.011
	(0.014)	(0.016)	(0.013)	(0.015)	(0.013)	(0.028)
Legislative Professionalism	−0.672*	−0.779*	−0.658	−0.776*	−0.494	−0.745
	(0.385)	(0.405)	(0.404)	(0.408)	(0.461)	(0.593)
Neighbors' Adoptions	0.217**	0.036	0.165**	0.002	0.167 **	0.008
	(0.036)	(0.045)	(0.034)	(0.043)	(0.034)	(0.071)
Time	0.326**	0.334**	0.357**	0.361**	0.349 **	1.064**
	(0.116)	(0.120)	(0.122)	(0.126)	(0.125)	(0.286)
Time Squared	−0.014	−0.006	−0.017	−0.009	−0.014	−0.068**
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.030)
Has this Provision			0.378**	0.172*	0.331 **	0.263
			(0.095)	(0.104)	(0.146)	(0.178)
Constant	−2.736**	−2.263**	−2.680**	−2.348**	−2.677 **	−5.500**
	(0.471)	(0.535)	(0.449)	(0.502)	(0.444)	(0.946)
Fixed Effects by:	*None*	*Prov.*	*None*	*Prov.*	*Other Prov.*	*Prov.*
χ^2 statistic (FE = 0)		78.59		113.33	34.60	121.65
p value		0.00		0.00	0.00	0.00
Observations	3873		4224			

Notes: Fixed effects' coefficients not reported. ** indicates $p \leq .05$; * $p \leq .10$.
Standard errors calculated by clustering on state.

Table 5: Analysis of Obesity Legislation Components Adopted per Year

	Discrete - EHA		Total Number	
	First	**Repeated**	**Neg. Bin.**	**OLS**
% Overweight BMI	4.752	4.030*	4.706**	2.694
	(2.935)	(2.177)	(2.091)	(1.950)
% Obese BMI	−6.974	−5.406	−4.693	−4.310
	(5.231)	(3.765)	(3.628)	(3.459)
Liberal Ideology	−0.041**	−0.013	−0.021	−0.005
	(0.019)	(0.016)	(0.017)	(0.014)
Unified Republican Gov't	−1.528**	−1.224**	−1.233**	−1.026**
	(0.454)	(0.335)	(0.329)	(0.341)
Divided Government	−0.464	−0.276	−0.452*	−0.608*
	(0.304)	(0.219)	(0.240)	(0.344)
Total Population	0.065**	0.073**	0.075**	0.102**
	(0.029)	(0.028)	(0.017)	(0.028)
Personal Income	−0.012	−0.045*	−0.029	−0.041*
	(0.028)	(0.026)	(0.028)	(0.024)
Legislative Professionalism	−0.637	−1.059	−0.648	0.106
	(1.059)	(1.141)	(0.778)	(1.052)
Neighbors' Adoptions	−0.074	−0.049	0.033	0.017
	(0.111)	(0.070)	(0.059)	(0.121)
Time	0.618**	0.599**	0.945**	0.064
	(0.232)	(0.185)	(0.280)	(0.165)
Time Squared	−0.013	−0.014	−0.053*	0.041*
	(0.031)	(0.021)	(0.029)	(0.020)
Has any Provision		0.173	0.341*	0.543*
		(0.195)	(0.190)	(0.294)
Constant	−2.470**	−1.263	−3.302**	0.939
	(1.037)	(0.916)	(1.029)	(0.627)
Observations	245		384	

Notes: ** indicates $p \leq .05$; * $p \leq .10$. Standard errors calculated by clustering on state.