# Specification Uncertainty and Model Averaging in State Policy Innovation Research 

by

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## Introduction

There is significant uncertainty in both the theory and measurement of explanatory variables in the practice of empirical research on state policy innovation. In this sub-field, there is much debate over such questions as, "What variables should be included?" and "How should those variables be measured?" Thus, there is a corresponding debate over the "right" or "best" statistical models to employ. This debate can have important implications, especially if the coefficients are significantly different across various models being considered. Given these implications, it is important to ask:

What can scholars do to handle specification uncertainty in state policy innovation research?

This paper argues for the use of Bayesian model averaging (BMA) techniques to handle the model specification uncertainty issue in state policy innovation studies. Although Bayesian model averaging is not a perfect solution, this paper will show that it is an improvement upon current approaches in the literature. The paper will use the model averaging techniques as presented by Bartels (1997). ${ }^{1}$ To demonstrate the utility of the model averaging approach, the paper will re-analyze five earlier policy innovation studies that did not use any model averaging techniques (Wong and Shen 2001b, Mintrom 1997, Mooney \& Lee 1995, Berry \& Berry 1992, and Berry \& Berry 1990). ${ }^{2} \square$ My previous study with Wong (2001b), on the adoption of charter school legislation, will

[^1]be the primary illustrative example. Model averaging techniques will also be run on the other two data sets, however, to show the broad applicability of the technique.

The paper is organized into five sections. In Section I, a theoretical background is provided. The research techniques and methodological approaches currently used in the sub-field of state policy innovation research are evaluated. In Section II the theory of Bayesian model averaging is introduced as a complementary addition to present practices. Section III presents a step-by-step approach for the application of the BMA in policy innovation studies, focusing on the author's earlier study of charter school law adoption. Section IV examines the BMA results from the charter school analyses, as well as results from BMA re-analysis of four additional state policy innovations: pre-Roe abortion regulation reform (Mooney and Lee 1995), consideration of school choice (Mintrom 1997), adoption of lotteries (Berry and Berry 1990), and various tax law adoptions (Berry and Berry 1992). Section V concludes the paper with an evaluation of the promises and limitations of further application of Bayesian model averaging techniques to state policy innovation research.

## I. THEORY BUILDING

## Why it's difficult to empirically study state policy innovation

Though they pose different methods for studying the processes of agenda setting, policy formulation, and ultimately policy adoption, scholars agree that these policy processes are quite complex (e.g. Kingdon 1984, Baumgartner and Jones 1993; Cohen, March and Olsen 1972). The process of policy adoption in the fifty United States is no exception - a multitude of factors can contribute to the adoption of innovative policies.

As noted by Kingdon (1984), even for those who are intimately involved in the policy process, it is often not easy to determine exactly why a certain policy was adopted when it was.

If it is hard for those with a birds-eye view to figure out what's driving policy innovation, it is even more difficult for a detached researcher who wishes to carry out empirical research on state policy innovation. To illustrate these difficulties, let us consider an example. Typically, researchers of state policy innovation will identify a policy adoption of interest and have a priori some idea of a few important factors that led to the policy's adoption. The researcher can tell a plausible story about how the policy came about, and now he/she hopes to support that story with empirical evidence. At this point, researchers are faced with several important methodological challenges.

First, given that the policy adoption process is so complex, it is likely that in addition to the researcher's story there are several (maybe many) other plausible stories that can be told. Indeed, the garbage can model of Cohen, March, and Olsen (1972) and its extension in Kingdon's (1984) discussion of separate streams, emphasize that policies emerge from multiple actors acting within a variety of contexts. For the empirical researcher of state policy innovation, then, the first difficulty is trying to figure out what independent variables (beyond the initial variable of interest) should be accounted for. This may not be a straightforward task. For example, the researcher may have a theoretically grounded hypothesis that Republican party control in a state will increase the likelihood of a state to adopt a certain policy. But the researcher may not have as much knowledge about the other possible explanatory variables. Is that policy also affected by interest group activity? Wealth levels in the state? Public opinion of state
residents? National trends? Regional activity? The list of possible variables could go on (and in fact it does since the policy process is so hard to nail down), but the point is made: a good degree of uncertainty is involved in the determination of explanatory variables in state policy innovation research. ${ }^{3}$

The second major challenge state policy researchers must overcome involves measurement error and the choice of proxy variables. Assuming that researchers are able to identify a thorough set of explanatory variables likely to explain state adoption of a given policy, the task of measuring those variables remains. As with virtually all other empirical research in the social sciences, measuring the variables of interest across states is often fraught with difficulty. In the policy process, where so much can happen "behind closed doors" or "under the table," it is impossible to measure all of the variables of true interest. The answer to this problem is usually the introduction of proxy variables. Proxies, however, are not always available and even if they are, they may not be close enough to the actual measure of interest. In sum, measurement difficulties are a second source of significant uncertainty.

## Present methodological practices in state policy innovation research

Following Walker (1969) and Gray's (1973) pioneering studies, scholars of American state politics have been empirically studying these two questions: "Why do some states act as pioneers by adopting new programs more readily than others?" and "How do these new forms of service or regulation spread among the American states?"

[^2](Walker 1969, p. 881). As summarized in Berry (1994), the determinants of state policy innovation can be generally classified into three categories: internal, regional diffusion, and national interaction.

The significant methodological advance in state policy innovation research has been Berry and Berry's $(1990,1992)$ introduction of event history analysis (EHA). Unlike earlier studies, which relied predominantly on factor analysis techniques (e.g. Nice 1994), research utilizing EHA can evaluate the impact of internal, regional, and national effects simultaneously (Berry 1994). Event history analysis is a method of pooled, cross-sectional time series, and it has allowed for the use of more sophisticated models to explain adoption of innovations (e.g. Berry and Berry 1990, 1992, Mooney and Lee 1995, Hays and Glick 1997, Mintrom 1997, and Mintrom and Vergari 1998).

Although EHA has been a breakthrough for policy innovation research, it is not without its drawbacks. Probably the most important limitation in EHA analyses is the modeling of the dependent variable as a dichotomous $(0,1)$ variable. ${ }^{\text {A }}$ dichotomous dependent variable is methodologically convenient, but limited in two ways. First, it doesn't allow for any variation across policies. States must either adopt ( $=1$ ) or not (=0), and there is no middle ground. This is inconsistent with the actual policy adoption process. Much political bargaining in the state house, after all, is not designed to stop a bill from passing, but to alter the nature of the bill before it is voted upon. In the case of charter school legislation, for instance, there are clearly "strong" and "weak" laws

[^3](Hassel 1999, Finn, et. al. 2000). Looking only at adoption of a law does not account for this variance. ${ }^{6} \square$

A related problem with the dichotomous dependent variable is that implicit in such a model is the assumption that the policy being adopted is the same across all states and all years (across all "state-years" in the terminology of EHA). This assumption, as discussed at length by Glick and Hays (1991), is a tenuous one, as it ignores the processes of "reinvention" and "evolution." Policy evolution and reinvention occurs over time, as states see what other states have done and adjust accordingly. Returning again to the charter school example, a state such as Illinois which did not pass its charter school law until 1994, has the benefit of learning from earlier states (e.g. Minnesota and California) who had already begun the experiment. Similarly, reinvention may occur when a bill is passed initially as a trial run, with the real legislation coming in subsequent years. This is in fact the case with some charter school laws, as earlier versions allow for only a few charter schools and in later years this is expanded. The dichotomous dependent variable cannot capture these evolution and reinvention changes.

In addition to the difficulties related to the dichotomous dependent variable, and more relevant to the discussion of model averaging, EHA places a tremendous burden on the researcher to collect state-level data over time. The variables researchers would like to include in their models are often not available. Hays and Glick (1997) describe a typical problem when the write, "we employ national public opinion support for the right to die. Even though national opinion research on this issue is spotty at best, state-level

[^4]data - although ideal - would be all but impossible to collect" (503). Caveats such as these appear in the theory-building sections of all state policy innovation studies. ${ }^{\text {Biven }}$ these data limitations, what do researchers do in practice? As coined by Mooney and Lee (1995), one common approach is to turn to the "usual suspects," a set of variables that are readily available by state and by year. The usual suspects include measures such as political party strength, population, wealth, political ideology, and degree of urbanization. The explanatory variables of interest are added to these controls. The state policy innovation researcher thus ends up with a set of potential explanatory variables. $\mathrm{He} /$ she must then decide which ones to include in the EHA model.

The reported models of published EHA policy innovation models have included a diverse set of explanatory variables (Table 1). Although some of the usual suspects (e.g. per capita income, election year, and party control) appear in most of the six models recorded in Table 1, there is much variation in the rest of the variables included. To be sure, part of this differentiation is due to variations in the policy being studied, i.e. what would affect the adoption of lotteries might not affect school choice adoption. But part of the variation is also due to researcher preferences about what to include and what to throw out of their final (reported) model.

If one pays careful attention to the footnotes of policy innovation studies using the EHA approach, it is evident that the process for deciding which variables to include in the final reported model(s) is similar to that of the applied econometrician as described by Leamer (1983): "The econometric art as it is practiced at the computer terminal involves

[^5]fitting many, perhaps thousands, of statistical models. One or several that the researcher finds pleasing are selected for reporting purposes" (36). Wintrom (2000) notes that "in preliminary analyses, in addition to these state politics variables [included in his model], [he] worked with a measure of the Ranney competition index (Bibby and Holbrook 1996, 105) and the Wright, Erikson, and McIver (1985) state ideology scores ... in all cases the results failed to meet any test of statistical significance" (207, footnote 15). In Hays and Glick (1997), it is noted that "several variants on the state courts variable were also tried ... [but] none of these variables performed any better than the number of cases in the previous year" (514, footnote 3). Wong and Shen (2001b) note a number of "preliminary" analyses that occurred before the final model was arrived at.

As these examples illustrate, state policy innovation research in practice involves consideration of a number of possible combinations of explanatory variables. The present method of dealing with these considerations is to justify a set of assumptions for inclusion/exclusion of variables, include notes to report any other notable models that were considered, and then settle on a final model(s) to report. In light of this present method, Bayesian model averaging seems a useful tool to introduce.

## II. THEORY OF BAYESIAN MODEL AVERAGING

## Appropriateness of BMA for policy innovation research

The history of BMA (as discussed in Hoeting, et. al. 1999), dates back to Barnard (1963) and was developed chiefly by economists in the 1970s (e.g. Leamer 1978). It has been used in a number of non-political science applications. It surfaced relatively recently in a debate between economists on the effectiveness of concealed-handgun laws. ${ }^{9}$ Since its introduction to political science by Bartels (1997), BMA is starting to appear in published political science articles. Two recent articles in Political Science \& Politics on the 2000 presidential election have used BMA in the election forecasting problem (Bartels and Zaller 2001; Erikson, Bafumi, and Wilson 2001).

It is likely that BMA may gain appeal in other sub-fields as well. As stated by Erikson, Bafumi, and Wilson, "BMA is intuitively appealing because it allows researchers to harness the predictive power of a series of regression models rather than rely on one model alone" (815). Or put another way, 64 or 96 regressions are better than 1. State policy innovation research, which focuses on the "coefficients of a linear regression model," (645) is a good candidate for the application of BMA. Researchers want to make inferences from these coefficients, e.g. a positive coefficient on the income variable means wealthier states are more likely to adopt this policy. It is therefore important to know, "How confident can I be in making inferences from my coefficient estimate?" BMA can help state policy researchers answer this question by putting the key

[^6]casual variable into a number of different models and seeing how it performs across them.

Further, with readable and detailed accounts of BMA provided by Bartels (1997) and Bartels and Zaller (2001), it is an approach that need not remain mysterious. Bartels and Zaller's non-technical description makes the case for BMA: ${ }^{1}$
"To understand our argument, it suffices for the nontechnical reader to understand two general principles. First, when plausible alternative models produce different results, it is important to recognize those differences - and the differences in the models that produced them - as a significant source of uncertainty in our statistical inferences, including out-of-sample forecasts. Rather than trusting (and touting) the results of any one model as if they were the final word, analysts should base their conclusions (whether formally or informally) on the range of evidence provided by plausible alternative models.

The second general principle of Bayesian model averaging is that the results of alternative models should figure more or less heavily in this synthesis depending, at least in part, on how well they fit the data. If, by some appropriate criterion, one model works better than another, then the results it generates should be given correspondingly more (though never total) credence. All reasonable models, even those that perform poorly, deserve at least some weight" (Bartels and Zaller 2001, p. 11).

## Statistical framework of BMA

What does this discussion of BMA mean in practice for state policy researchers?
First, the researcher can run a number of models $M_{\mathrm{j}}$ and obtain a set of parameters and variances for each model. The researcher can then determine how much credence to give each model by using the posterior probability, $\pi_{\mathrm{j}}$. The researcher sums over all the models, and the mean of the unconditional posterior distribution is:

$$
\begin{equation*}
E(\boldsymbol{\beta} \mid \mathbf{X}, \mathbf{y}) \equiv \mathbf{b}=\sum \pi_{\mathrm{j}} \mathbf{b}_{\mathrm{j}} \tag{1}
\end{equation*}
$$

and the variance of the unconditional posterior distribution is:

$$
\begin{equation*}
V(\boldsymbol{\beta} \mid \mathbf{X}, \mathbf{y})=\sum \pi_{\mathrm{j}} \mathrm{~V}\left(\mathbf{b}_{\mathrm{j}}\right)+\sum \pi_{\mathrm{j}} \mathrm{~V}\left(\mathbf{b}_{\mathrm{j}}-\mathbf{b}\right)^{2} \tag{2}
\end{equation*}
$$

[^7]where $\pi_{\mathrm{j}}=p\left(M_{\mathrm{j}} \mid \mathbf{X}, \mathbf{y}\right)$ is the posterior probability for model $M_{\mathrm{j}}$. ${ }_{\mathrm{To}}$ calculate the posterior model probabilities, the "Bayes factor" is introduced. The Bayes factor, $B_{\mathrm{ij}}$, is the ratio of marginal likelihoods for model $M_{\mathrm{i}}$ and model $M_{\mathrm{j}}$ and is calculated by: 2
\[

$$
\begin{equation*}
B_{\mathrm{ij}} \equiv p\left(\mathbf{X}, \mathbf{y} \mid M_{\mathrm{i}}\right) / p\left(\mathbf{X}, \mathbf{y} \mid M_{\mathrm{j}}\right) \tag{3}
\end{equation*}
$$

\]

The Bayes factor can be calculated readily using the Bayesian Information Criterion
(BIC). ${ }^{3}$ Calculated using the BIC, the Bayes factor is:

$$
\begin{equation*}
B_{\mathrm{j} 0} \equiv \mathrm{e}^{\wedge}\left(-.5 \mathrm{BIC}\left(M_{\mathrm{j}}\right)\right) \tag{4}
\end{equation*}
$$

Using the Bayes factor, "we can solve for the model posterior probability for any
particular Model $M_{\mathrm{i}}$ as a function of the complete set of model prior probabilities and Bayes factors:" ${ }^{4}(\mathrm{p} .648)$

$$
\begin{equation*}
\pi_{\mathrm{i}}=B_{\mathrm{i} 0} \pi_{\mathrm{i}}^{0} / \sum B_{\mathrm{j} 0} \pi_{\mathrm{j}}^{0} \tag{5}
\end{equation*}
$$

To calculate $\pi_{\mathrm{i}}$, this paper will make the assumption of "uniform model priors," $\left(\pi^{0}{ }_{1}=\ldots\right.$ $\left.\pi_{j}^{0}=\ldots=\pi_{J}^{0}=1 / \mathrm{J}\right)$. In this case, "the posterior probability for each model is simply
proportional to the corresponding Bayes factor:" (p. 648)

$$
\begin{equation*}
\pi_{\mathrm{i}}=B_{\mathrm{i} 0} / \sum_{B_{\mathrm{j} 0}} \tag{6}
\end{equation*}
$$

If there is good reason to believe (a priori) that certain models are more appropriate than others, the assumption of uniform model priors can be modified. ${ }^{15}$ The uniform model

[^8]priors assumption is appropriate, however, when all models are considered to be equally plausible. As discussed earlier, this is usually the case for state policy researchers: there are many plausible models and no convincing reason to choose one over the other. Once $\pi_{\mathrm{i}}$ has been solved for in equation [6], it can then be used to calculate the weighted means and variances.

## III. IMPLEMENTING BAYESIAN MODEL AVERAGING TECHNIQUES

To demonstrate how BMA can be implemented naturally in the course of state policy innovation research, I draw on a previous analysis (Wong and Shen 2001b) of state adoption of charter school legislation. The original analysis focused on the impact of electoral dynamics, specifically election timing and party control. In this revised BMA analysis, however, electoral dynamics are not established a priori as the explanatory variables of interest. Rather, the analysis will start with a series of theoretically grounded hypotheses, proceed to explain what data is available to test the hypotheses, and then utilize BMA to fit a number of plausible models. Using this approach will allow the discussion to be generalized to any policy adoption of interest.

The first step in utilizing BMA is no different than established practice: identify a set of variables which the researcher believes may have a potential impact on the policy adoption. It should be emphasized that theoretical assumptions about data, measurement, and variable construction are no less important in a BMA framework. In establishing the set of relevant explanatory variables, a useful step is differentiating independent variables on the basis of their projected impact on the outcome variable. This paper will categorize two types of independent variables - "essential" variables which are thought to be quite relevant to the policy's adoption, and "plausible" variables which are thought to be
somewhat relevant to the policy's adoption. Making such a distinction will facilitate the BMA process because it determines which variables (the essential ones) will reside permanently in the model and which variables will be shuffled in and out (the plausible ones) as a variety of model specifications are considered. I now turn to the case of charter school legislation to discuss variable selection.

## Selection of explanatory variables for analysis of charter school adoption

## Choosing initial set of variables and identifying alternative measures

In many accounts of charter school opposition, teacher unions are discussed as a key player (e.g. Hassel 1999, Finn, et. al. 2000, Maranto, et. al. 2000). Teacher unions generally oppose charter schools because charters are not required to bargain with the union and can thus hire non-union teachers. Teachers' unions not only have an incentive to fight charters, they also have the organizational capacity and strong state and national networks to facilitate sustained policy drives. The teacher union variable (union) is derived from Michael Mintrom's mid-1990s national survey of teacher union activity in the states. Mintrom uses this measure in his analysis of school choice $(1997,2000)$.

The second variable designated as essential is the percentage of education revenue provided by the state (revenue). Public school revenue comes from state and local sources, with the federal government contributing about 7 percent. The balance between state and local sources, however, is not constant across states. It makes sense that states who have a larger stake in the public schools will both have an easier time innovating (i.e. more control over what happens) and more of an interest in innovating (since they

[^9]have more financial responsibility). This variable was also included in Mintrom's analysis, and has been examined by the author in other analyses (Wong and Shen 2001c).

A third essential variable is the level of private school activity in the state. Charter schools often resemble private schools and a strong private school market would indicate a friendly environment for charter schools to open and operate. Charter schools, as independent entities, must coordinate a number of services in the same ways that private schools do (Hassel 1999). Thus, a strong private school network would facilitate charter school operations. ${ }^{7}$ Phere are two possible ways to measure private school strength. First is a measure of the number of private schools out of all schools in the state (private). Every other year since 1993, the Department of Education has conducted a survey of the Private School Universe. The second measure for private school climate is the percent of students in non-public schools (enrprv), a proxy for private school enrollment. ${ }^{1}$ $\qquad$

Preliminary testing will determine which measure of private school activity should be used.

The fourth and final essential variable is a control for time. As discussed by Beck,
Katz, and Tucker (1998) among others, time controls must be added to ensure that the

[^10]independent variables are not correlated with the hazard rate, i.e. to control for the fact that more states will adopt over time simply because more time has passed. This is especially important in the case of charter schools because there is good reason to believe that a national push for charter legislation affected state adoption. Specifically, in 1994 the Department of Education started offering federal grants to states to help them develop charter school programs. Such national pushes, increasing in strength over time, would be captured by the time controls. In state policy innovation research, time has been modeled as either a series of time dummies (Mintrom 1997) or as a trend variable (Mooney and Lee 1995; Hays and Glick 1997). In this paper, time (trend) will be modeled as the square root of the number of years since the year of the first adoption, i.e. the number of years since 1991. This is similar to the trend variable used in Mooney and Lee (1995) and exploratory analysis demonstrated that it is better suited for the charter school data than a series of time dummies. ${ }^{1 \square}$

In addition to the four essential variables, nine variables will be considered as plausible. For each of these variables, a story can be told about why they should be included in the model. Also for each variable, however, objections can be raised as to their relevance to the adoption of a charter school law. Each of these plausible variables will be discussed briefly. $\square$

In many states, charter schools are seen as a way to address the needs of special student populations (Wong and Shen 2001b). In Texas, for example, there is special emphasis placed on serving at-risk students. This is encouraged by state legislation that

[^11]allows for "an unlimited number of charter schools that would serve students at risk of failure or dropping out of school." Given charter schools' potential to serve at risk student populations, the percentage of minorities and poverty-stricken students in a state might make a state more likely to adopt charter legislation. These two variables (minority, and poverty) are thus included as plausible variables.

By creating a competitive market for students, charter schools are also seen as a way to address failing school districts (Nathan 1996, Rofes 1998). In states where the schools are performing at a lower level, there might be a greater perceived need for change such as charter school legislation. While measuring school performance is not an easy task, two potential measures are high school completion rates (complete) and average high school SAT scores (avgsat). Neither of these measures are ideal, but there are few uniform measures available. NAEP data was attempted in other analysis (Wong and Shen 2000), but it is not available for every year and only for a select group of states. Thus, these are two of the best possible measures and will both be considered as potential plausible variables.

Since charter schools are not always politically neutral, it is important to consider political variables as well. Four political variables considered here are Democratic party control (ran4yr), governor's election year (govVote), state house election year (hosVote), and non-election year (offyear). While these are plausible variables, it is not entirely clear in which direction we should expect their sign. On one hand, charter schools may be seen as a Republican-friendly issue and a controversial issue that

[^12]lawmakers would rather pass when not up for election. On the other hand, however, lawmakers may see charter schools as an innovative policy suggestion that might win them voters if promoted during a campaign. As demonstrated by former President Clinton's vocal support for charter schools, they may also be a non-partisan issue in some states.

Policy innovation studies traditionally include a state-to-state diffusion variable (diffuse). This study follows in that tradition, as it is plausible that states saw their neighbors enact charter school legislation and decided to follow suit. The diffuse variable might not be as strong, though, if the national push for charter schools (discussed earlier) was strong. In that case, states would not be learning from their immediate neighbors, but from states across the nation. The ambiguity surrounding the diffusion effect also surrounds the effects of income on charter school adoption. ${ }^{2}$ Income and population often fall into the "usual suspects" category, and with good reason. It is plausible that larger and richer states may have more resources to experiment with innovative educational policies such as charter schools. But recalling the discussion of special needs students, if charter schools are designed to serve at-risk populations such as students in poverty, higher income in the state may not be a good indicator of the likelihood of adopting charter legislation.

Implementing any type of school reform, including charter schools, involves working through the bureaucracy of the state's education system. The more "red tape"

[^13]that is involved, the less likely it is for a state to adopt an innovative education policy.
One way to measure the red tape is the level of state central control. The more centralized a state, the less likely it is that localities will be able to innovate. A proxy for centralization (distsize) can be created by taking the number of school districts and dividing it by the number of public school students in the state. Finally, charter schools often face financial challenges (Hassel 1999). Since teacher salaries comprise the bulk of a school's operating expenses, it might stand to reason that states with higher average teacher salaries (salary) will be environments in which charter schools are less likely to open.

## Determining which alternative measures to use

Given the available data just discussed, three decisions must be made regarding alternative measures of desired variables. First, should private school activity be measured with the percent of private schools in the state (private) or a proxy for the percentage of students in private schools (enrprv)? Second, should achievement be measured by the high school completion rate (complete) or a state's average SAT scores (avgsat)? Third, which political timing variables (hosVote, govVote, and offyear) should be included in the model?

To make each of these three determinations, preliminary tests were run in which the competing measures were included separately in models including only the four important variables. For example, the first comparison involved running a model with the important variables and private; then running a model with the important variables and enrprv. The BIC of the two models were then compared and the model with the smaller BIC was selected. This methodology led to the selection of enrprv over private, avgsat
over complete, and hosVote instead of govVote and offyear. ${ }^{4}$ After these preliminary tests, then, the final set of relevant variables is determined (summarized in Table 2).

## IV. BMA RESULTS

## Implementing BMA: 64 models are good, but 512 are better

The thrust of most BMA articles is simple: more models are better. ${ }^{2}$ The results from the BMA analysis of charter school adoption demonstrate why this is true. First, I run a set of 64 models by including the avgsat, minority, and poverty variables in all models and varying only the final six independent variables. To demonstrate clearly what is going on "under the hood" in a BMA analysis, I present results from all 64 models in Table 3. The last column (far right hand side) indicates the weight of each model. It is evident that many of the models carry little weight. This is important to note, especially since two of the variables (ran4yr and distsize) are only significant in models whose weights are small. If I were reporting only one or two models, I might (either randomly or selectively) choose one of the models in which ran4yr or distsize is significant. My resulting inferences - that party control or centralization of the state's education system were significant factors affecting the adoption of charter legislation - would be incorrect. I could avoid this error by placing these single models in the context of the entire 64. In this broader context, it can be seen that overall, the only significant variables are the trend variable (positive as expected) and the minority variable (also positive as expected). The lesson to be learned is that 64 models are better than 1 .

[^14]But there is more to the story: while 64 models are good, 512 models are better still. To arrive at 512 models, I now allow all nine plausible variables to be shuffled in and out of the model. The results from the 512 models are summarized in Table 4, comparing them to the original results and those from the 64 models. When compared to the 64 models, it can be seen that the coefficient for the minority variable is significantly smaller when tested in 512 as compared to 64 models. In light of the results from the 512 models, the percentage of minority students seems less important to charter school adoption.

This demonstration of BMA in the study of charter school policy adoption has shown that inferences made after running only a few models are not as good as those made after more models have been run. BMA thus allows researchers to be more confident in their coefficient estimates. This paper now turns to four additional data sets to further illustrate the use of BMA in state policy innovation research.

## Additional illustrations of BMA in state policy innovation research

Given the extensive discussion on the details of integrating BMA into the study of charter school law adoption, this section will move quickly to the results from an application of BMA to four additional policy innovation studies: Mooney and Lee's (1995) study of pre-Roe abortion legislation, Mintrom's (1997) study of consideration of school choice, Berry \& Berry's (1990) study of lotteries, and Berry \& Berry's (1992) study of tax adoption.

Mooney and Lee's dependent variable is change in abortion regulation before the Roe vs. Wade decision. They introduce 12 independent variables to explain this policy change. Of these variables, three stand out as the most well defended (and therefore most essential to include in the model): the percent of females in the workforce (fem), the percent of Catholics and Protestants (relig), and the time trend control (trend). ${ }^{\sqrt{6}}$ This leaves nine variables to consider across 512 models: per capita personal income (pcpi), level of urbanization (urban), number of medical doctors per 100,000 population (md), a piecewise 1968 M.D. interaction (piecemd), Savage innovativeness index 1978 (savage), party competition index (holbrook), election index (elindex), New Deal policy-based index of liberalism 1983 (rosenstone), and average regional permissiveness (nvallag). Two sets of 512 models were considered: one with time modeled as a trend variable (as originally computed by Mooney and Lee) and one incorporating time as a series of yearspecific time dummies. ${ }^{27}$

When compared to the original results from Mooney and Lee, the results from the BMA analysis over 512 models are striking (Table 5). In the model with Mooney and Lee's original time trend variable, all but one of the other variables that were significant in Mooney and Lee's reported model (relig, trend, md, piecemd, nvallag, holbrook, and elindex) are no longer significant at the .05 level. The lone exception is the female workforce variable (which remains significant and approximately the same magnitude). In the models in which year-specific time dummies were included, the results are slightly different. The measure of regional permissiveness (nvallag) remains significant and its

[^15]magnitude is greater than the original model reported in Mooney and Lee. The election index variable also remains significant, though its magnitude is greatly reduced.

Turning to Mintrom's (1997) data, the dependent variable is legislative consideration of school choice. Mintrom's variables of interest are two that relate to policy entrepreneurs. Mintrom identifies the presence of a policy entrepreneur (entre) and the activity score of entrepreneurs (entre_sc). Mintrom's other independent variables are the percent of education revenue provided by the state (starevpc), presence of a Republican governor (gov_r1), house election year (elect), Republican control of the legislature (rep_leg), relative change in student test scores using the standardized education index (sei_diff), percent of private schools in the state (priv), previous adoption of other education reforms (reform80), union activity (union), and diffusion (diffuse). A series of dummy variables for years, from 1987 through 1992, is also included in the model. Based on the discussion in Mintrom's article, the essential variables will be union, diffuse, and the six year-specific dummies. This leaves the other nine variables to be combined into 512 different models. Models were run with time modeled as a series of year-specific time dummies (as Mintrom originally used) and with a time trend variable.

Comparing the BMA analysis of Mintrom's data to the original reported models (Table 6), the results from the 512 models provide support for Mintrom's original inferences. This is true whether time is incorporated as time dummies or as a trend variable. The variables that were significant in the original reported models - presence of an entrepreneur, entrepreneur score, house election year, diffuse, and the time dummies remain significant (although their magnitude is diminished) in the averaged results.

Berry and Berry's (1990) dependent variable is state adoption of a lottery. They consider seven independent variables in their model: the fiscal health of state government, as measured by the "ratio of total-state-revenues-minus-state-spending to total spending ${ }^{, 18}$ (fiscal); the degree of single-party control in the state legislature (party); whether or not it is a gubernatorial election year (elect1); whether or not it is neither the year of an election or the year right after an election (elect2); real per capita income (income); the percentage of the state's population adhering to fundamentalist religions (religion); and the number of neighboring states that have already adopted the innovation (neighbors). For the re-analysis, I added a time trend variable, modeled in the same manner as in Mooney \& Lee (1995). With only seven independent variables in the original analysis, the determination of essential variables was made somewhat difficult, i.e. the small number of final-model variables suggests that important filtering of variables has already occurred. Nevertheless, for the purpose of this study, three variables were designated as essential: income, neighbors, and the time trend variable. This left five plausible variables, resulting in averages over 32 models. ${ }^{9}$

When the results of the BMA analysis are compared to Berry \& Berry's original results, one sees a fairly consistent pattern (Table 7). The gubernatorial election year variable remains significant and positive, though magnitude of the coefficient drops in the BMA analysis. Similarly, the income, party, religion, and neighbors variables also remain significant and of the same sign found in the original model. There are two significant differences in the new analysis. First, the elect2 variable (measuring whether or not it is an offyear) loses significance. This may be due to the introduction of the time

[^16]trend variable. More interestingly, the fiscal variable (measuring state fiscal health) becomes significant and inversely related with the likelihood to adopt a lottery. This is consistent with Berry \& Berry's first hypothesis, that "the worse the fiscal health of a state's government $\ldots$ the more likely it is to adopt a lottery.'


Berry \& Berry's (1992) study shifts its focus to state tax innovation. They look at several related dependent variables: adoption of an income tax in the period 1916-37, gasoline tax in the period 1919-29, any tax between 1919-39, and any tax between 196071. The set of independent variables is quite similar to those used in Berry \& Berry (1990). New control variables added for the tax study include a measure of state urbanization (urban) and the number of registered motor vehicles (cars). Two variations on the party variable are also introduced: the extent to which government institutions are controlled by a liberal party (ideology) and the degree to which a single party controls government institutions (instit). The same three essential variables used in 1990 (income, previousad, and income) are used for the 1992 re-analysis.

The reanalysis of state income tax adoption (Table 8a) reveals that most of the original findings hold up. In the original model (2), income, elect1, and ideology all remain significant. The magnitude of the coefficients for income and ideology drops, but the magnitude on elect1 actually increases substantially. When the fiscal variable is included, as it is in the original model (1), fiscal turns out to be significant and inversely related to adoption. As with the 1990 study, this finding on the fiscal variable gives additional support to Berry \& Berry's hypothesis. Several other variables, however, do not remain significant in the new analysis. Most striking are the elect2 (offyear) variable,

[^17]which changes its sign (from negative to positive) and the ideology variable, which changes sign and loses significance.

When looking at adoption of a gasoline tax (Table 8b), we find a similar pattern around the fiscal variable. In the reanalysis, it is significantly and inversely related to adoption. Also in the reanalysis, the "cars" variable, which measures the number of registered motored vehicles, drops significance and magnitude. The neighbors variable similarly drops in magnitude and loses significance at the .05 level. Personal income remains unchanged, with virtually the same magnitude in both original and revised BMA analyses.

Finally, the reanalysis of adoption of any tax (Table 8c) suggests that party control (measured by the ideology and instit variables) may play a stronger role in tax adoption than the original results found. In models (5) and (7), the ideology/instit variable moves from slightly positive, but not statistically significant, to negative and significant. The fiscal and elect1 variables also remain significant in models (5) and (6), though magnitude is smaller in the BMA set of results.

Discussion of the new results - What should we take away from this reanalysis?
The previous section has walked quickly through the results presented in Tables 5-8. Several comments can be made about the comparisons between the original and reanalyzed results.

First, it is evident that BMA is not a tool for "knocking down" earlier findings. Rather, as evident in the analysis of Mintrom's data and many of Berry \& Berry's models, BMA is a tool for "propping up" findings from a single (or a few) regressions. It
is striking, for instance, to see the relative consistency between Berry \& Berry's original results (which lacked even a time trend variable) and the new BMA results.

Second, a comparison across the data sets suggests that BMA analysis can be useful in revealing the most salient (and perhaps best measured) variables. In the Berry \& Berry analysis, we see that after BMA analysis, the fiscal variable becomes significant and more strongly inversely related to adoption. It is probably not a coincidence that the fiscal variable is also related to the authors' first and very well grounded hypothesis. At the same time, variables that are less well measured turn out to be less significant after we use the BMA approach. The "cars" variable, for instance, is no longer significant in the BMA set of results. It may not be a coincidence either that this variable, which is a proxy for "the demand for highways," is a few steps removed from the actual phenomenon it is supposed to capture. ${ }^{3}$ In short, the BMA approach seems to produce the result it is supposed to: it gives us more information on which empirical relationships we should be confident in, and which ones we should hedge our bets on.

A similar trend can be found in a comparison of the Mintrom vs. Mooney and Lee models. Recall from the previous section that while the BMA results supported most of Mintrom's original findings, the reanalysis of Mooney \& Lee's data produced a set of coefficients that while generally of the same sign, lost magnitude and statistical significance. What can explain these differences? One explanation may be measurement error. Mintrom collects his policy entrepreneur data from an original, national survey of the fifty states. Such targeted data collection allows Mintrom to isolate the factors he wants to measure: the presence of policy entrepreneurs in the policy domain of school choice. Mooney and Lee, on the other hand, must rely on theoretically justified proxies.

While these are certainly the best data available, there are necessary limitations on their applicability. Their measure for the "strength of the medical establishment in a state," for instance, is the number of medical doctors per 100,000 population (p. 616). Without a national survey (to ask specifically about medical establishment strength), Mooney and Lee's data is open to more potential measurement error.

Finally, the Mooney results suggest that the specification of time controls (as either year-specific dummies or a time trend variable) can significantly affect the inferences one makes. Researchers might do well to consider models of both sort, if applicable, and report differences between the two.

## V. CONCLUDING DISCUSSION

This paper has introduced a Bayesian Model Averaging approach to help researchers of state policy innovation gain leverage over the model specification uncertainty that is inherent in state policy research. By moving step-by-step through the BMA process as used to study the adoption of charter school legislation, it has been shown that the method is both appropriate and relatively easy to implement in the context of policy innovation event history analysis. By further testing BMA on several prominent previous EHA analyses, the paper has illustrated that BMA can be generally applied to a variety of EHA models in the state policy innovation sub-field. It is hoped that future EHA models in the context of state policy innovation will consider BMA as a complementary approach to current methodological practice. ${ }^{3 \square}$

[^18]Although BMA has proven useful in the state policy innovation context, significant challenges still remain. First, the choice of variables to consider in the BMA process is still a determination that the researcher must struggle with. ${ }^{3}$ This is less a statistical, and more a theoretical concern. As is done in the state policy literature cited in this paper, researchers must review the relevant theory and policy process in order to determine what variables are important or plausible. This determination is a critical one, since (as illustrated in this paper), the important variables are left in the model at all times, while the plausible variables are shuffled in and out.

Second, BMA cannot make up for poorly measured variables. It remains the case that better data produces better results. BMA may in fact make measurement error more visible if certain variables lose significance when modeled over a large number of regression models. The tactic of turning to sub-state units to increase the number of observations and reduce measurement error remains a good suggestion for state policy adoption researchers.

Third, there is a potential "loophole" in the BMA process that must be considered. This involves the use of model priors. In this paper, uniform model priors were assumed throughout. But if researchers believe a priori that certain models should be weighted more heavily, they can adjust the weights to match these beliefs. The process of deciding what weights to apply may turn into a process similar to the very process this approach is

[^19]designed to avoid: the process of trying to figure out which models are the "right" ones to pay attention to.

Fourth, the BMA reanalysis implies that future state policy innovation research would do well to follow along the Mintrom (2000) approach, which "adds meat" to the bare bones numbers. If nothing else, BMA reminds us of the limits of the EHA approach. It reminds us that to truly grasp the state policy innovation process, we must dig deeper into the process itself. It is not an original recommendation to choose carefully measured independent variables instead of rough proxies, but the BMA analysis presented in this paper makes it clear why variable measurement and model specification matter so much.

It was stated at the beginning of the paper that the adoption of innovative policies by states is a messy and complicated process. As long as this process remains somewhat mysterious, the statistical models and variables used by researchers will likewise remain uncertain. Researchers must put together the policy innovation puzzle from a number of disparate pieces. BMA, at the end of day, simply allows us to be more sure of which empirical relationships we should emphasize and which ones we should be cautious about. Although it does not entirely clear up our understanding of the policy process puzzle, the use of Bayesian Model Averaging can give researchers a better framework for sorting out through the pieces of the state policy innovation puzzle.

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|  | Berry and Berry (1990) | $\begin{aligned} & \text { Berry and Berry } \\ & \text { (1992) } \end{aligned}$ | Mooney and Lee (1995) - Model 1 | Mintrom (1997) | Hays and Glick (1997) | Wong and Shen (2001) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Dependent variable: Policy adoption of interest ${ }^{\text {a }}$ | State lottery | a.) Gasoline tax and <br> b.) Individual income tax | Abortion regulation reform, pre-Roe | a.) Consideration of school choice; b.) Adoption of school choice | Living-will laws | Charter school legislation |
| Years of interest for risk set | 1964-1986 | $\begin{aligned} & \text { a.) 1911-1929; b.) } \\ & 1916-1937 \text { and } 1960- \\ & 1971 \\ & \hline \end{aligned}$ | 1966-1972 | 1987-1992 | 1976-1991 | 1992-1999 |
| General Explanatory Variables seen in many EHA state policy innovation models | Per capita income, real \$ in previous year <br> (INCOMEREL) | Per capita income, real ${ }^{\text {b }}$ <br> (INCOME) | Per capita income, real \$ <br> (PCPI) | - | Per capital income, real \$ | Per capital income, real \$ <br> (INCOME) |
|  |  | Level of state urbanization (URBAN) | Urbanization (URBAN) |  |  | Population (POPULATION) |
|  | Fiscal health in previous year (FISCAL) | Fiscal health (FISCAL) |  |  |  |  |
|  | Non-election year for state offices (ELECT2) | Non-election year for state offices (ELECT2) | Election activity index, based on gov. and both houses (ELINDEX) | State house election year <br> (ELECT) |  | State house election year <br> (HOSVOTE) |
|  | Gubernatorial election year <br> (ELECT1) <br> Number of neighbors already adopting (NEIGHBOR) | Gubernatorial election year <br> (ELECT1) |  |  |  |  |
|  |  | Percentage of neighbors already adopting (PREVIOUSAD) |  | Percentage of neighbors already considering / adopting (DIFFUSE) | Number of neighbors already adopting | Percentage of neighbors already adopting (DIFFUSE) |
|  |  | Liberalness of state government, using own 0-1 index of gov. and both houses (IDEOLOGY) | Factor analytic index of New Deal policy liberalism using Rosenstone's (1983) index <br> (ROSENSTONE) | Republican control of state legislature (REPLEG) | Ideological liberalism from Erickson, Wright, and Mclver (1993) |  |


|  | Berry and Berry (1990) | Berry and Berry (1992) | Mooney and Lee (1995) - Model 1 | Mintrom (1997) | Hays and Glick (1997) | Wong and Shen (2001) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Level of single party control <br> (PARTY) | Level of single party control <br> (PARTY) | Interparty competition, using Holbrook and Van Dunk's (1993) index (HOLBROOK) | Republican governor (GOVR1) | Interparty competition, measured by Ranney party control index in Bibby et al. (1983) | Interparty competition, measured by Ranney party control index constructed by authors ${ }^{\text {h }}$ (RAN4YR) |
|  |  | Historical degree of control x single party control (HISTCONT) |  |  | Democratic control of gov. and both houses |  |
|  |  |  | Innovativeness of state, using Savage's (1979) index (SAVAGE) |  | Innovativeness of state, using Walker's (1969) index |  |
|  |  |  | Time trend: Square root of distance in years from 1970 (TREND) | Maturation effects: dichotomous $(0,1)$ time variables |  |  |
| Theoryspecific variables | Proportion of population adhering to fundamentalist religions (RELIGION) | Number of registered motor vehicles (CARS) | Pct. Roman Catholic or fundamentalist Protestant (RELIG) |  | Pct. belonging to Catholic Church ${ }^{9}$ |  |
|  |  |  | Pct of state's females $>16$ in workforce in $1970^{\circ}$ <br> (FEM) | Pct. of educ. funding by the state (STAREVPC) | Pct. of population $>25$ with at least 12 yrs of education | Pct. of educ. funding by the state (REVENUE) |
|  |  |  | Number of physicians per 100,000 population ${ }^{\text {d }}$ (MD) | Relative change in student (SAT/ACT) test scores (SEIDIFF) | Number of court cases in state in prev. year | Student (SAT) test scores <br> (AVGSAT) |
|  |  |  | Permissiveness of region on abortion policy, using Gutmann scale developed by authors (NVALLAG) | Pct. of private schools in state (PRIV) | Number of court cases in all states in prev. year | Pct. of school-aged population in nonpublic schools (ENRPRV) |
|  |  |  |  | Other educ. reforms adopted in 1980s (REFORM80) | Number of articles on living wills or right-todie in popular publications | High school completion rate (COMPLETE) |

## Table 1. Variables used in selected EHA state policy innovation models

| $\begin{aligned} & \text { Berry and Berry } \\ & \text { (1990) } \end{aligned}$ | Berry and Berry (1992) | Mooney and Lee (1995) - Model 1 | Mintrom (1997) | Hays and Glick (1997) | Wong and Shen (2001) |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Opposition of teachers' union (UNION) <br> Policy entrepreneur present in state ${ }^{e}$ (ENTRE) <br> Activity score of policy entrepreneur ${ }^{\text {e }}$ (ENTRESC) | National public opinion support for right-to-die |  |

 other years. After adoption in year $t$, the state $i$ is no longer included in the risk set and thus is no longer observed in subsequent years. ${ }^{\text {b }}$ a.) INCOMEREL: state per capita income in the nearest "even" decade year divided by national per capita income in the same year; b.) INCOMECON: state per capita income divided by the implicit price deflator for personal consumption expenditures, to convert income to 'constant' 1982 dollars ${ }^{\text {c. The }} 1970$ value was used for all years in the EHA. d. A piecewise regression approach was used to isolate the medical doctors effect to the years 1966-1968, but not after. ${ }^{\text {e. See Mintrom (1997) for a full discussion }}$ of these variables. . This is also included as an interaction with the level of single party control. ${ }^{\text {g. To eliminate the effect of the Catholic variable after 1984, it is }}$
 used.

| Four essential variables |  |  |
| :---: | :---: | :---: |
| Name | Definition | Data source |
| union | Dichotomous $(1,0)$ indicating the presence of union opposition to school choice | Michael Mintrom's national survey on school choice (see Mintrom 2000 for survey details) |
| revenue | Percentage of education revenue provided by state | U.S. Department of Education (DOE), Common Core of Data (CCD), various years |
| enrprv | 1 - (Number of students enrolled in public schools / Number of school aged children) | U.S. Census Bureau and U.S. DOE Digest of Education Statistics, various years |
| trend | Square root of number of years since 1991 (first year in which a state adopts a charter law) | Calculated by author |
|  |  |  |
| Nine plausible variables |  |  |
| Name | Definition | Data source |
| avgsat | Difference between state average SAT score and national average | U.S. DOE, Digest of Education Statistics, various years |
| minority | Percentage of public school students who are minorities | U.S. DOE, Digest of Education Statistics, various years |
| poverty | Percentage of public school students who are below the poverty level | U.S. DOE, Digest of Education Statistics, various years |
| diffuse | Percentage of neighboring states who have previously adopted charter legislation | Calculated by author |
| ran4yr | Ranney party index, lagged 4 years | Calculated by author (see Wong and Shen 2001 for details) |
| hosVote | Dichotomous ( 1,0 ) variable indicating a state house election year | Calculated by author using data from the Council of State Governments |
| income | Per capita income, in real \$ | U.S. Census Bureau |
| distsize | Ratio of number of students to number of school districts | Calculated by authors, using data from U.S. DOE, Digest of Education Statistics |
| salary | Average teacher salary, adjusted for regional cost of living (1998) | American Federation of Teachers |


| Model | Intercept | union | revenue | enrprv | trend ${ }^{\text {a }}$ | avgsat | minority ${ }^{\text {b }}$ | poverty | diffuse | ran4yr ${ }^{\text {c }}$ | hosVote | income | distsize ${ }^{\text {d }}$ | salary | weight |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Coeff. $\\| \text { S.E. }$ | -5.9591 4.3574 | 0.6438 0.7658 | -0.1907 1.6994 | 4.2016 6.1053 | 1.1088 0.3113 | 0.6397 5.7433 | 4.9795 1.9744 | -3.3154 5.4008 | $\begin{gathered} -3.83 \mathrm{E}- \\ 06 \\ 2.63 \mathrm{E}-06 \end{gathered}$ | $-2.55 \mathrm{E}-05$ $1.21 \mathrm{E}-05$ | -0.0080 0.0199 | $7.86 \mathrm{E}-07$ $4.42 \mathrm{E}-06$ | $-6.02 \mathrm{E}-11$ $2.96 \mathrm{E}-11$ | $7.21 \mathrm{E}-07$ $1.04 \mathrm{E}-06$ |  |
| 1 | -5.8607 | 0.6357 | -0.1864 | 4.5330 | 1.1156 | 0.5622 | 4.9863 | -3.5307 | - | - | - | - |  |  | 0.8635 |
|  | 4.2314 | 0.7506 | 1.6882 | 6.2772 | 0.3113 | 5.8028 | 1.9669 | 5.1473 | - | - | - | - |  | - |  |
| 2 | -8.6501 | 0.6389 | -0.0213 | 1.8829 | 1.1157 | 2.4250 | 5.1727 | -3.5284 | - | - | - | - |  | 4.32E-05 | 0.0152 |
|  | 5.8814 | 0.7543 | 1.7264 | 7.3297 | 0.3107 | 6.4000 | 1.9852 | 5.1187 | - | - | - | - | - | $6.28 \mathrm{E}-05$ | - |
|  | -4.8582 | 0.8901 | -0.1762 | 3.6143 | 1.2052 | -0.6260 | 7.5546 | -8.1888 | - | - | - | - | -6.45E-05 | - | 0.0000 |
| 3 | 4.2343 | 0.7774 | 1.6243 | 6.2072 | 0.3220 | 5.8595 | 2.4148 | 5.9753 | - | - | - | - | $3.24 \mathrm{E}-05$ | - | - |
| 4 | -6.4193 | 0.6225 | -0.1720 | 4.2752 | 1.1013 | 0.7427 | 4.7720 | -2.5646 | - | - | - | $9.98 \mathrm{E}-06$ | - | - | 0.0699 |
|  | 5.4656 | 0.7558 | 1.6898 | 6.4832 | 0.3218 | 5.9235 | 2.3618 | 7.8592 | - | - | - | $6.15 \mathrm{E}-05$ | - | - | - |
| 5 | -5.7898 | 0.6487 | -0.1721 | 4.6575 | 1.1132 | 0.5075 | 4.9319 | -3.4147 | - | - | -0.1596 | - | - | - | 0.0459 |
|  | 4.2397 | 0.7516 | 1.6889 | 6.2783 | 0.3097 | 5.8187 | 1.9698 | 5.1591 | - | - | 0.3967 | - | - | - | - |
| 6 | -3.4907 | 0.5397 | 0.3241 | 4.7415 | 1.0110 | $-1.1606$ | 6.0679 | -2.0696 | - | -3.2979 | - | - | - | - | 0.0000 |
|  | 4.4413 | 0.7570 | 1.6796 | 6.3652 | 0.3114 | 5.9354 | 2.1822 | 5.2786 | - | 1.5371 | - | - | - | - | - |
| 7 | -6.3270 | 0.5861 | -0.2802 | 3.7002 | 1.4949 | 0.8023 | 5.0897 | -3.3633 | -1.3996 | - | - | - | - | - | 0.0000 |
|  | 4.3109 | 0.7465 | 1.6859 | 6.2490 | 0.4223 | 5.9231 | 1.9501 | 5.0666 | 0.9733 | - | - | - | - | - | - |
| 8 | -5.9671 | 0.8829 | -0.1130 | 2.5377 | 1.2029 | 0.1441 | 7.5470 | -8.0663 | - | - | - | - | -6.30E-05 | 1.69E-05 | 0.0000 |
|  | 6.0002 | 0.7776 | 1.6509 | 7.4382 | 0.3218 | 6.5532 | 2.4078 | 5.9724 | - | - | - | - | $3.28 \mathrm{E}-05$ | $6.45 \mathrm{E}-05$ | - |
| 9 | -8.5588 | 0.6422 | -0.0218 | 1.9025 | 1.1194 | 2.4123 | 5.2293 | -3.7686 | - | - | - | -2.48E-06 | - | 4.39E-05 | 0.0008 |
|  | 6.3414 | 0.7588 | 1.7269 | 7.3451 | 0.3252 | 6.4055 | 2.4728 | 8.0762 | - | - | - | $6.44 \mathrm{E}-05$ | - | $6.55 \mathrm{E}-05$ | - |
| 10 | -8.5953 | 0.6528 | -0.0076 | 2.0001 | 1.1135 | 2.3871 | 5.1175 | -3.4078 | - | - | -0.1611 | - | - | 4.33E-05 | 0.0009 |
|  | 5.8942 | 0.7553 | 1.7267 | 7.3311 | 0.3090 | 6.4201 | 1.9881 | 5.1314 | - | - | 0.3972 | - | - | $6.28 \mathrm{E}-05$ | - |
| 11 | -4.9069 | 0.5392 | 0.3768 | 3.2614 | 1.0119 | -0.2058 | 6.0987 | -2.0063 | - | -3.2301 | - | - | - | $2.17 \mathrm{E}-05$ | 0.0000 |
|  | 6.1088 | 0.7583 | 1.6990 | 7.6899 | 0.3114 | 6.5714 | 2.1772 | 5.2770 | - | 1.5557 | - | - | - | $6.39 \mathrm{E}-05$ | - |
| 12 | -9.6887 | 0.5935 | -0.0767 | 0.6538 | 1.5082 | 3.1560 | 5.3584 | -3.4316 | -1.4475 | - | - | - | - | $4.94 \mathrm{E}-05$ | 0.0000 |
|  | 6.2066 | 0.7496 | 1.7301 | 7.3840 | 0.4242 | 6.6865 | 1.9860 | 5.0331 | 0.9828 | - | - | - | - | $6.47 \mathrm{E}-05$ | - |
| 13 | $-5.8209$ | 0.8711 | -0.1407 | 3.1664 | 1.1818 | -0.2914 | 7.1967 | -6.5839 | - | - | - | $1.68 \mathrm{E}-05$ | -6.50E-05 | - | 0.0000 |
|  | 5.5199 | 0.7822 | 1.6276 | 6.4301 | 0.3301 | 6.0103 | 2.7312 | 8.3461 | - | - | - | $6.12 \mathrm{E}-05$ | $3.25 \mathrm{E}-05$ | - | - |
| 14 | -4.7709 | 0.9074 | -0.1632 | 3.7751 | 1.2002 | -0.6770 | 7.5296 | -8.1375 | - | - | -0.1912 | - | -6.50E-05 | - | 0.0000 |


| Model | Intercept | union | revenue | enrprv | trend ${ }^{\text {a }}$ | avgsat | minority ${ }^{\text {b }}$ | poverty | diffuse | ran4yr ${ }^{\text {c }}$ | hosVote | income | distsize ${ }^{\text {d }}$ | salary | weight |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 15 | 4.2453 | 0.7787 | 1.6243 | 6.2099 | 0.3200 | 5.8775 | 2.4200 | 5.9924 | - | - | 0.4008 | - | 3.25E-05 |  |  |
|  | -3.2786 | 0.7157 | 0.2175 | 3.7269 | 1.1041 | -1.6388 | 7.5106 | -5.6655 | - | -2.4450 | - |  | -4.64E-05 | - | 0.0000 |
|  | 4.4214 | 0.7779 | 1.6459 | 6.3048 | 0.3248 | 5.9347 | 2.4329 | 6.0985 | - | 1.6738 |  |  | $3.36 \mathrm{E}-05$ |  |  |
| 16 | -5.2579 | 0.8173 | -0.2441 | 3.0189 | 1.4928 | -0.4167 | 7.2947 | -7.3672 | -1.0970 | - | - | - | -5.90E-05 | - | 0.0000 |
|  | 4.3035 | 0.7732 | 1.6306 | 6.1903 | 0.4242 | 5.9488 | 2.3731 | 5.8602 | 0.9900 | - | - | - | $3.25 \mathrm{E}-05$ | - | - |
| 17 | -6.4237 | 0.6335 | -0.1551 | 4.3636 | 1.0972 | 0.7110 | 4.6873 | -2.3122 | - | - | -0.1635 | 1.13E-05 | - | - | 0.0036 |
|  | 5.4785 | 0.7569 | 1.6905 | 6.4871 | 0.3196 | 5.9406 | 2.3692 | 7.9025 | - |  | 0.3974 | 6.17E-05 |  | - |  |
| 18 | -2.9061 | 0.5460 | 0.3167 | 4.9981 | 1.0224 | -1.3574 | 6.3055 | -3.0277 | - | -3.3412 | - | -9.74E-06 | - | - | 0.0000 |
|  | 5.7943 | 0.7573 | 1.6802 | 6.5647 | 0.3212 | 6.0529 | 2.6682 | 8.0891 | - | 1.5664 | - | $6.22 \mathrm{E}-05$ | - | - | - |
| 19 | -6.9547 | 0.5720 | -0.2660 | 3.4196 | 1.4771 | 1.0334 | 4.8664 | -2.3238 | -1.4004 | - | - | $1.09 \mathrm{E}-05$ | - | - | 0.0000 |
|  | 5.6069 | 0.7516 | 1.6872 | 6.4581 | 0.4314 | 6.0858 | 2.3179 | 7.7666 | 0.9728 | - | - | $6.18 \mathrm{E}-05$ | - | - | - |
| 20 | -3.3199 | 0.5572 | 0.3678 | 4.9000 | 1.0046 | -1.2978 | 6.0428 | -1.9067 | - | -3.3812 | -0.2360 | - | - | - | 0.0000 |
|  | 4.4606 | 0.7582 | 1.6790 | 6.3631 | 0.3085 | 5.9632 | 2.1881 | 5.2912 | - | 1.5491 | 0.4030 |  | - | - | - |
| 21 | -6.2649 | 0.5998 | -0.2594 | 3.8362 | 1.4897 | 0.7584 | 5.0379 | -3.2706 | -1.3926 | - | -0.1490 | - | - | - | 0.0000 |
|  | 4.3181 | 0.7477 | 1.6877 | 6.2551 | 0.4212 | 5.9367 | 1.9539 | 5.0766 | 0.9733 | - | 0.3983 | - | - | - | - |
| 22 | -4.0488 | 0.5636 | 0.1921 | 3.7771 | 1.3454 | -0.8715 | 6.0647 | -1.9165 | -1.2600 | -3.0866 | - | - | - | - | 0.0000 |
|  | 4.5024 | 0.7605 | 1.6821 | 6.3584 | 0.4248 | 6.0280 | 2.1658 | 5.2277 | 1.0198 | 1.5365 | - | - | - | - | - |
| 23 | -6.4415 | 0.8700 | -0.1019 | 2.4559 | 1.1851 | 0.2120 | 7.2690 | -6.8429 | - | - | - | $1.31 \mathrm{E}-05$ | -6.38E-05 | $1.27 \mathrm{E}-05$ | 0.0000 |
|  | 6.4438 | 0.7816 | 1.6476 | 7.4608 | 0.3310 | 6.5777 | 2.7578 | 8.4576 | - | - | - | 6.43E-05 | 3.31E-05 | 6.78E-05 | - |
| 24 | $-5.8784$ | 0.9002 | -0.1007 | 2.6999 | 1.1981 | 0.0940 | 7.5210 | -8.0132 | - | - | -0.1911 | - | -6.36E-05 | $1.68 \mathrm{E}-05$ | 0.0000 |
|  | 6.0153 | 0.7788 | 1.6504 | 7.4466 | 0.3197 | 6.5757 | 2.4131 | 5.9908 | - | - | 0.4010 | - | $3.29 \mathrm{E}-05$ | 6.45E-05 | - |
| 25 | -3.7109 | 0.7137 | 0.2349 | 3.2887 | 1.1034 | $-1.3388$ | 7.5020 | -5.6153 | - | -2.4309 | - | - | -4.60E-05 | 6.52E-06 | 0.0000 |
|  | 6.1803 | 0.7783 | 1.6586 | 7.6669 | 0.3248 | 6.6463 | 2.4317 | 6.1173 | - | 1.6825 | - | - | 3.39E-05 | 6.51E-05 | - |
| 26 | -6.9224 | 0.8081 | -0.1489 | 1.4718 | 1.4993 | 0.7784 | 7.3082 | -7.2174 | -1.1336 | - | - | - | -5.69E-05 | $2.41 \mathrm{E}-05$ | 0.0000 |
|  | 6.2791 | 0.7727 | 1.6633 | 7.4806 | 0.4252 | 6.7860 | 2.3603 | 5.8354 | 0.9987 | - | - | - | 3.30E-05 | 6.59E-05 | - |
| 27 | -8.5588 | 0.6541 | -0.0079 | 2.0082 | 1.1149 | 2.3821 | 5.1402 | -3.5040 | - | - | -0.1607 | -9.88E-07 | - | $4.36 \mathrm{E}-05$ | 0.0001 |
|  | 6.3595 | 0.7600 | 1.7269 | 7.3491 | 0.3229 | 6.4272 | 2.4798 | 8.1195 | - | - | 0.3978 | $6.46 \mathrm{E}-05$ | - | $6.54 \mathrm{E}-05$ | - |
| 28 | -4.2122 | 0.5496 | 0.3768 | 3.3843 | 1.0318 | -0.3354 | 6.5105 | -3.6274 | - | -3.2896 | - | -1.66E-05 | - | 2.63E-05 | 0.0000 |
|  | 6.6755 | 0.7582 | 1.7018 | 7.6905 | 0.3235 | 6.5731 | 2.7197 | 8.2362 | - | 1.5819 | - | 6.47E-05 | - | 6.63E-05 | - |
| 29 | -9.6068 | 0.5963 | -0.0766 | 0.6718 | 1.5119 | 3.1396 | 5.4054 | -3.6360 | -1.4476 | - | - | -2.13E-06 | - | $4.99 \mathrm{E}-05$ | 0.0000 |
|  | 6.6819 | 0.7541 | 1.7303 | 7.4021 | 0.4388 | 6.7014 | 2.4447 | 7.9785 | 0.9829 | - | - | $6.44 \mathrm{E}-05$ | - | $6.71 \mathrm{E}-05$ | - |
| 30 | -4.7501 | 0.5569 | 0.4200 | 3.4048 | 1.0055 | -0.3297 | 6.0725 | -1.8372 | - | -3.3151 | -0.2368 | - | - | 2.19E-05 | 0.0000 |
|  | 6.1273 | 0.7594 | 1.6980 | 7.6936 | 0.3085 | 6.6027 | 2.1831 | 5.2910 | - | 1.5670 | 0.4033 | - | - | 6.39E-05 | - |


| Model | Intercept | union | revenue | enrprv | trend ${ }^{\text {a }}$ | avgsat | minority ${ }^{\text {b }}$ | poverty | diffuse | ran4yr ${ }^{\text {c }}$ | hosVote | income | distsize ${ }^{\text {d }}$ | salary | weight |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 31 | -9.6460 | 0.6086 | -0.0559 | 0.7833 | 1.5032 | 3.1320 | 5.3057 | -3.3335 | -1.4410 | - | -0.1511 | - |  | 4.95E-05 | 0.0000 |
|  | 6.2189 | 0.7508 | 1.7316 | 7.3882 | 0.4230 | 6.7052 | 1.9897 | 5.0440 | 0.9828 | - | 0.3988 | - |  | $6.47 \mathrm{E}-05$ |  |
| 32 | -6.0395 | 0.5634 | 0.2770 | 1.7949 | 1.3576 | 0.5185 | 6.1399 | -1.8671 | -1.2997 | -2.9972 | - |  |  | $2.90 \mathrm{E}-05$ | 0.0000 |
|  | 6.3903 | 0.7611 | 1.7088 | 7.7431 | 0.4269 | 6.8061 | 2.1636 | 5.2210 | 1.0267 | 1.5561 | - | - | - | $6.55 \mathrm{E}-05$ |  |
| 33 | -5.8460 | 0.8857 | -0.1221 | 3.2724 | 1.1747 | -0.3055 | 7.1292 | -6.3373 | - | - | -0.1991 | -6.57E-05 | -6.57E-05 | - | 0.0000 |
|  | 5.5359 | 0.7836 | 1.6275 | 6.4357 | 0.3273 | 6.0308 | 2.7370 | 8.3855 | - | - | 0.4019 | $3.26 \mathrm{E}-05$ | 3.26E-05 | - |  |
| 34 | -3.1657 | 0.7165 | 0.2159 | 3.7764 | 1.1060 | -1.6793 | 7.5520 | -5.8353 | - | -2.4559 | - | -4.63E-05 | -4.63E-05 |  | 0.0000 |
|  | 5.8592 | 0.7783 | 1.6470 | 6.5248 | 0.3318 | 6.0904 | 2.8118 | 8.4026 | - | 1.7144 | - | $3.38 \mathrm{E}-05$ | 3.38E-05 | - | - |
| 35 | -6.2565 | 0.7982 | -0.2107 | 2.5720 | 1.4666 | -0.0367 | 6.9500 | -5.7694 | -1.0953 | - | - | -5.95E-05 | -5.95E-05 | - | 0.0000 |
|  | 5.6454 | 0.7779 | 1.6336 | 6.4108 | 0.4306 | 6.1345 | 2.6672 | 8.2180 | 0.9884 | - | - | $3.26 \mathrm{E}-05$ | 3.26E-05 | - | - |
| 36 | -3.1252 | 0.7313 | 0.2526 | 3.9043 | 1.0957 | -1.7431 | 7.4842 | -5.5322 | - | -2.5153 | -0.2299 | - | -4.63E-05 | - | 0.0000 |
|  | 4.4410 | 0.7790 | 1.6461 | 6.3068 | 0.3220 | 5.9602 | 2.4387 | 6.1195 | - | 1.6861 | 0.4047 | - | $3.37 \mathrm{E}-05$ |  |  |
| 37 | -5.1756 | 0.8356 | -0.2253 | 3.1891 | 1.4849 | -0.4620 | 7.2711 | -7.3315 | -1.0888 | - | -0.1835 | - | -5.96E-05 | - | 0.0000 |
|  | 4.3138 | 0.7746 | 1.6314 | 6.1971 | 0.4227 | 5.9654 | 2.3792 | 5.8769 | 0.9903 | - | 0.4024 | - | $3.26 \mathrm{E}-05$ |  | - |
| 38 | -3.7612 | 0.6960 | 0.1216 | 3.0875 | 1.3751 | -1.3698 | 7.2792 | -5.0170 | -1.0522 | -2.3266 | - | - | -4.17E-05 | - | 0.0000 |
|  | 4.4794 | 0.7735 | 1.6520 | 6.2943 | 0.4285 | 6.0135 | 2.4025 | 6.0140 | 1.0255 | 1.6700 | - | - | 3.40E-05 | - | - |
| 39 | -2.8672 | 0.5624 | 0.3611 | 5.1015 | 1.0131 | -1.4480 | 6.2278 | -2.6568 | - | -3.4132 | -0.2330 | -7.59E-06 | - | - | 0.0000 |
|  | 5.8061 | 0.7589 | 1.6800 | 6.5700 | 0.3176 | 6.0788 | 2.6737 | 8.1365 | - | 1.5748 | 0.4036 | $6.25 \mathrm{E}-05$ |  | - | - |
| 40 | -6.9902 | 0.5834 | -0.2420 | 3.5120 | 1.4695 | 1.0237 | 4.7776 | -2.0607 | -1.3942 | - | -0.1547 | 1.26E-05 | - | - | 0.0000 |
|  | 5.6204 | 0.7528 | 1.6890 | 6.4655 | 0.4294 | 6.1017 | 2.3279 | 7.8175 | 0.9727 | - | 0.3994 | $6.21 \mathrm{E}-05$ | - | - | - |
| 41 | -3.6405 | 0.5683 | 0.1879 | 3.9510 | 1.3531 | $-1.0226$ | 6.2171 | -2.5566 | -1.2572 | -3.1147 | - | -6.65E-06 | - | - | 0.0000 |
|  | 5.9108 | 0.7611 | 1.6826 | 6.5603 | 0.4323 | 6.1820 | 2.6039 | 7.9778 | 1.0213 | 1.5625 | - | $6.25 \mathrm{E}-05$ | - | - | - |
| 42 | -3.8859 | 0.5826 | 0.2450 | 3.9612 | 1.3339 | -0.9955 | 6.0387 | -1.7624 | -1.2505 | -3.1740 | -0.2282 | - | - | - | 0.0000 |
|  | 4.5205 | 0.7617 | 1.6834 | 6.3629 | 0.4220 | 6.0536 | 2.1730 | 5.2422 | 1.0202 | 1.5498 | 0.4046 |  | - | - | - |
| 43 | -6.4336 | 0.8848 | -0.0863 | 2.6010 | 1.1777 | 0.1724 | 7.1965 | -6.5799 | - | - | -0.1976 | 1.53E-05 | -6.45E-05 | 1.19E-05 | 0.0000 |
|  | 6.4642 | 0.7831 | 1.6465 | 7.4705 | 0.3282 | 6.6039 | 2.7629 | 8.4959 | - | - | 0.4021 | $6.46 \mathrm{E}-05$ | 3.32E-05 | 6.78E-05 | - |
| 44 | -3.5455 | 0.7152 | 0.2347 | 3.3154 | 1.1075 | -1.3713 | 7.5900 | -5.9741 | - | -2.4518 | - | -3.99E-06 | -4.57E-05 | 7.72E-06 | 0.0000 |
|  | 6.7490 | 0.7783 | 1.6596 | 7.6769 | 0.3324 | 6.6636 | 2.8313 | 8.4916 | - | 1.7185 | - | $6.54 \mathrm{E}-05$ | $3.42 \mathrm{E}-05$ | 6.80E-05 | - |
| 45 | -7.3388 | 0.7970 | -0.1420 | 1.4029 | 1.4808 | 0.8533 | 7.0770 | -6.1780 | -1.1276 | - | - | $1.13 \mathrm{E}-05$ | -5.75E-05 | $2.06 \mathrm{E}-05$ | 0.0000 |
|  | 6.7246 | 0.7766 | 1.6604 | 7.5002 | 0.4352 | 6.8149 | 2.6977 | 8.3245 | 0.9978 | - | - | $6.47 \mathrm{E}-05$ | 3.32E-05 | $6.90 \mathrm{E}-05$ | - |
| 46 | -3.5662 | 0.7293 | 0.2702 | 3.4561 | 1.0950 | -1.4361 | 7.4748 | -5.4789 | - | -2.5017 | -0.2300 | - | -4.59E-05 | 6.65E-06 | 0.0000 |
|  | 6.1970 | 0.7793 | 1.6586 | 7.6772 | 0.3220 | 6.6742 | 2.4377 | 6.1402 | - | 1.6941 | 0.4047 | - | $3.40 \mathrm{E}-05$ | $6.51 \mathrm{E}-05$ | - |
| 47 | -6.8399 | 0.8269 | -0.1307 | 1.6436 | 1.4916 | 0.7355 | 7.2826 | -7.1781 | -1.1256 | - | -0.1833 | - | -5.75E-05 | $2.41 \mathrm{E}-05$ | 0.0000 |


| Model | Intercept | union | revenue | enrprv | trend ${ }^{\text {a }}$ | avgsat | minority ${ }^{\text {b }}$ | poverty | diffuse | ran4yr ${ }^{\text {c }}$ | hosVote | income | distsize ${ }^{\text {d }}$ | salary | weight |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 48 | 6.2936 | 0.7740 | 1.6638 | 7.4901 | 0.4236 | 6.8072 | 2.3663 | 5.8535 | 0.9989 |  | 0.4027 |  | $3.31 \mathrm{E}-05$ | 6.59E-05 |  |
|  | -4.7699 | 0.6918 | 0.1653 | 2.1044 | 1.3806 | -0.6504 | 7.2725 | -4.9116 | -1.0787 | -2.2965 | - | - | -4.06E-05 | $1.45 \mathrm{E}-05$ | 0.0000 |
|  | 6.4403 | 0.7736 | 1.6717 | 7.7202 | 0.4297 | 6.8565 | 2.3944 | 6.0249 | 1.0342 | 1.6812 | - | - | $3.44 \mathrm{E}-05$ | 6.64E-05 | - |
| 49 | -4.1540 | 0.5666 | 0.4181 | 3.5159 | 1.0221 | -0.4368 | 6.4272 | -3.2412 | - | -3.3636 | -0.2312 | -1.43E-05 |  | $2.58 \mathrm{E}-05$ | 0.0000 |
|  | 6.6914 | 0.7599 | 1.7006 | 7.6991 | 0.3199 | 6.6042 | 2.7245 | 8.2835 |  | 1.5900 | 0.4040 | $6.49 \mathrm{E}-05$ |  | 6.63E-05 |  |
| 50 | -9.6353 | 0.6089 | -0.0559 | 0.7857 | 1.5037 | 3.1298 | 5.3118 | -3.3603 | $-1.4410$ |  | -0.1509 | -2.77E-07 |  | $4.96 \mathrm{E}-05$ | 0.0000 |
|  | 6.7016 | 0.7556 | 1.7315 | 7.4086 | 0.4367 | 6.7230 | 2.4545 | 8.0307 | 0.9828 | - | 0.3999 | $6.47 \mathrm{E}-05$ | - | $6.70 \mathrm{E}-05$ | - |
| 51 | -5.4035 | 0.5737 | 0.2816 | 1.9054 | 1.3768 | 0.3744 | 6.4901 | -3.2899 | -1.2983 | -3.0482 | - | $3.30 \mathrm{E}-05$ |  | $3.30 \mathrm{E}-05$ | 0.0000 |
|  | 6.9583 | 0.7611 | 1.7116 | 7.7496 | 0.4384 | 6.8138 | 2.6633 | 8.1232 | 1.0295 | 1.5804 |  | $6.78 \mathrm{E}-05$ |  | $6.78 \mathrm{E}-05$ | - |
| 52 | -5.8890 | 0.5831 | 0.3295 | 1.9673 | 1.3461 | 0.4078 | 6.1117 | -1.7043 | -1.2905 | -3.0869 | -0.2291 |  |  | $2.91 \mathrm{E}-05$ | 0.0000 |
|  | 6.4076 | 0.7623 | 1.7097 | 7.7510 | 0.4241 | 6.8355 | 2.1705 | 5.2372 | 1.0272 | 1.5688 | 0.4050 | - | - | $6.55 \mathrm{E}-05$ | - |
| 53 | -3.1514 | 0.7311 | 0.2530 | 3.8927 | 1.0952 | -1.7338 | 7.4746 | -5.4924 | - | -2.5128 | -0.2300 | $4.30 \mathrm{E}-07$ | -4.64E-05 | - | 0.0000 |
|  | 5.8723 | 0.7797 | 1.6472 | 6.5325 | 0.3284 | 6.1152 | 2.8166 | 8.4483 | - | 1.7234 | 0.4055 | $6.29 \mathrm{E}-05$ | 3.39E-05 |  | - |
| 54 | -6.3114 | 0.8136 | -0.1857 | 2.6796 | 1.4559 | -0.0325 | 6.8771 | -5.5018 | -1.0884 | - | -0.1935 | $1.94 \mathrm{E}-05$ | -6.02E-05 |  | 0.0000 |
|  | 5.6631 | 0.7795 | 1.6344 | 6.4195 | 0.4278 | 6.1546 | 2.6754 | 8.2682 | 0.9882 | - | 0.4040 | $6.21 \mathrm{E}-05$ | 3.27E-05 |  | - |
| 55 | -3.7525 | 0.6961 | 0.1214 | 3.0912 | 1.3753 | -1.3731 | 7.2822 | -5.0297 | -1.0522 | -2.3274 |  | -1.39E-07 | -4.17E-05 |  | 0.0000 |
|  | 5.9647 | 0.7744 | 1.6527 | 6.5102 | 0.4339 | 6.2022 | 2.7529 | 8.2973 | 1.0255 | 1.7072 | - | $6.30 \mathrm{E}-05$ | $3.41 \mathrm{E}-05$ |  | - |
| 56 | -3.6113 | 0.7132 | 0.1643 | 3.2815 | 1.3630 | $-1.4674$ | 7.2536 | -4.8907 | -1.0448 | -2.4016 | -0.2248 |  | -4.17E-05 | - | 0.0000 |
|  | 4.4981 | 0.7746 | 1.6535 | 6.3015 | 0.4258 | 6.0377 | 2.4095 | 6.0366 | 1.0261 | 1.6834 | 0.4062 | - | $3.40 \mathrm{E}-05$ | - | - |
| 57 | -3.6361 | 0.5856 | 0.2419 | 4.0688 | 1.3384 | -1.0868 | 6.1326 | -2.1591 | -1.2484 | -3.1904 | -0.2263 | -4.09E-06 | - | - | 0.0000 |
|  | 5.9241 | 0.7628 | 1.6842 | 6.5710 | 0.4286 | 6.2065 | 2.6122 | 8.0381 | 1.0214 | 1.5720 | 0.4056 | 6.28E-05 | - | - | - |
| 58 | -3.5022 | 0.7300 | 0.2699 | 3.4669 | 1.0965 | -1.4483 | 7.5090 | -5.6188 | - | -2.5096 | -0.2294 | -1.55E-06 | -4.58E-05 | 7.11E-06 | 0.0000 |
|  | 6.7640 | 0.7797 | 1.6590 | 7.6899 | 0.3290 | 6.6927 | 2.8355 | 8.5355 | - | 1.7271 | 0.4056 | $6.57 \mathrm{E}-05$ | $3.44 \mathrm{E}-05$ | 6.80E-05 | - |
| 59 | -7.3539 | 0.8128 | -0.1209 | 1.5565 | 1.4694 | 0.8269 | 6.9973 | -5.8917 | -1.1192 | - | -0.1906 | $1.39 \mathrm{E}-05$ | -5.83E-05 | 1.97E-05 | 0.0000 |
|  | 6.7465 | 0.7783 | 1.6601 | 7.5111 | 0.4323 | 6.8410 | 2.7053 | 8.3745 | 0.9974 | - | 0.4042 | $6.51 \mathrm{E}-05$ | 3.33E-05 | 6.89E-05 | - |
| 60 | -4.5862 | 0.6940 | 0.1661 | 2.1317 | 1.3859 | -0.6915 | 7.3655 | -5.3005 | -1.0801 | -2.3186 | - | -4.39E-06 | -4.03E-05 | 1.58E-05 | 0.0000 |
|  | 7.0016 | 0.7739 | 1.6729 | 7.7294 | 0.4379 | 6.8786 | 2.7736 | 8.3798 | 1.0354 | 1.7149 | - | $6.57 \mathrm{E}-05$ | $3.47 \mathrm{E}-05$ | 6.92E-05 | - |
| 61 | -4.6265 | 0.7092 | 0.2081 | 2.2905 | 1.3684 | -0.7415 | 7.2453 | -4.7794 | -1.0715 | -2.3733 | -0.2251 | - | -4.06E-05 | 1.46E-05 | 0.0000 |
|  | 6.4567 | 0.7746 | 1.6730 | 7.7331 | 0.4270 | 6.8834 | 2.4016 | 6.0501 | 1.0349 | 1.6941 | 0.4064 | - | $3.45 \mathrm{E}-05$ | 6.64E-05 | - |
| 62 | -5.3718 | 0.5919 | 0.3316 | 2.0613 | 1.3612 | 0.2938 | 6.3979 | -2.8734 | -1.2885 | -3.1259 | -0.2233 | -1.21E-05 | - | $3.24 \mathrm{E}-05$ | 0.0000 |
|  | 6.9761 | 0.7628 | 1.7121 | 7.7618 | 0.4346 | 6.8443 | 2.6708 | 8.1846 | 1.0297 | 1.5896 | 0.4061 | 6.52E-05 | - | $6.77 \mathrm{E}-05$ | - |
| 63 | -3.7676 | 0.7116 | 0.1665 | 3.2148 | 1.3603 | $-1.4076$ | 7.1999 | -4.6609 | -1.0455 | -2.3880 | -0.2260 | 2.52E-06 | -4.18E-05 | - | 0.0000 |
|  | 5.9801 | 0.7758 | 1.6541 | 6.5220 | 0.4303 | 6.2267 | 2.7606 | 8.3568 | 1.0257 | 1.7172 | 0.4074 | $6.33 \mathrm{E}-05$ | $3.42 \mathrm{E}-05$ | - | - |


| Model | Intercept | ion | revenue | enrprv | trend ${ }^{\text {a }}$ | avgsat | minority ${ }^{\text {b }}$ | povert | iffuse | ran4yr ${ }^{\text {c }}$ | hosVote | income | distsize ${ }^{\text {d }}$ | salary | weight |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 64 | -4.5628 | 0.7100 | 0.2082 | 2.3004 | 1.3702 | -0.7555 | 7.2776 | -4.9153 | -1.0718 | -2.3807 | -0.2243 | -1.53E-06 | -4.05E-05 | 1.51E-05 | 0.0000 |
|  | 7.0191 | 0.7753 | 1.6734 | 7.7444 | 0.4342 | 6.9078 | 2.7807 | 8.4387 | 1.0353 | 1.7245 | 0.4076 | 6.60E-05 | $3.48 \mathrm{E}-05$ | 6.92E-05 | - |

NOTES: First line of results for each model reports the coefficients for each independent variable. The second line reports the standard error of the coefficient estimate. All significant results (either $\mathbf{p}<.001, \mathrm{p}<.01$, or $\mathrm{p}<.05$ ) are printed in bold. See the following notes for specific discussion of significant levels. ${ }^{\text {a. }}$ The time trend variable was significant in all 64 models. In models 41-42,51-52,55,57,60,62-64, trend was sig. at $\mathrm{p}<.01$. In all other models, $\mathrm{p}<.001$. ${ }^{\text {b. The percent of }}$ minority students in public schools (minority) was also significant in all models. In models 4,9,17-19,27-29,39-41,49-50,57, and 62, p<.05. In all other models, $p<.01$. The ${ }^{\mathrm{c}}$. Democratic party control measure (ran4yr) was significant at $p<.05$ in models $6,11,18,20,22,28,30,32,39,41-42,49,51-52,57$, and 62 models. d. The number of students per school district (distsize) was significant at $p<.05$ in models $3,8,13-14,23-24,33$,and 43 . ${ }^{\text {e. As discussed in the paper, the average }}$ coefficients and standard errors are calculated by taking the averages over all 64 models, weighted by each model's posterior probability (under the assumption of uniform model priors).

| Results after using Bayesian Model Averaging Techniques over 512 Models |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | intercept | union | revenue | enrprv | trend | avgsat | minority | poverty | diffuse | ran4yr | hosVote | income | distsize | salary |
| Coeff. | -5.254 | 0.809 | 0.290 | 8.371 | 1.006 | -0.083 | 1.30E-11 | 0.013 | 0.000 | -0.029 | -0.011 | 6.33E-07 | -3.75E-07 | 1.05E-06 |
| Std. Err. | 1.478 | 0.716 | 1.556 | 5.964 | 0.288 | 0.125 | 4.27E-12 | 0.009 | 0.000 | 0.029 | 0.019 | $9.55 \mathrm{E}-07$ | 1.17E-06 | $2.47 \mathrm{E}-06$ |
| Min | -10.410 | 0.433 | -0.778 | 0.654 | 0.893 | -6.200 | 0.000 | -8.382 | -1.448 | -3.444 | -0.300 | -1.66E-05 | -6.57E-05 | -2.05E-05 |
| Max | -0.677 | 0.932 | 0.714 | 9.317 | 1.535 | 3.156 | 7.712 | 13.160 | 0.000 | 0.000 | 0.000 | $1.08 \mathrm{E}-04$ | 7.45E-06 | $4.99 \mathrm{E}-05$ |
|  |  |  |  | Results | after usi | $g$ Bayesia | n Model Av | veraging | Techniques | over 64 Mo | dels |  |  |  |
|  | intercept | union | revenue | enrprv | trend | avgsat | minority | poverty | diffuse | ran4yr | hosVote | income | distsize | salary |
| Coeff. | -5.959 | 0.644 | -0.191 | 4.202 | 1.109 | 0.640 | 4.980 | -3.315 | -3.83E-06 | -2.55E-05 | -0.008 | 7.86E-07 | -6.02E-11 | 7.21E-07 |
| Std. Err. | 4.357 | 0.766 | 1.699 | 6.105 | 0.311 | 5.743 | 1.974 | 5.401 | $2.63 \mathrm{E}-06$ | $1.21 \mathrm{E}-05$ | 0.020 | $4.42 \mathrm{E}-06$ | 2.96E-11 | 1.04E-06 |
| Min | -9.689 | 0.539 | -0.280 | 0.654 | 1.005 | -1.743 | 4.687 | -8.189 | -1.448 | -3.413 | -0.237 | -1.66E-05 | -6.57E-05 | $0.00 \mathrm{E}+00$ |
| Max | -2.867 | 0.907 | 0.420 | 5.102 | 1.512 | 3.156 | 7.590 | -1.704 | 0.000 | 0.000 | 0.000 | $1.94 \mathrm{E}-05$ | $0.00 \mathrm{E}+00$ | 4.99E-05 |
| NOTES: <br> percent of (1992-1999) <br> size, or s | ignificant private sch 9) instead ary variabl | results ools in the of the time es. | with 95\% e state (pri trend variab | confidence rivate), a m riable. The | e or better measure of original m | er) are in of high scho model did in | bold. In all mod ol completio include the | models, $\mathrm{n}=$ n (comple union, enro | $=287$. The o te), populatio lled in privat | riginal Wong on, election e schools | g and Shen off year, (enrprv), m | $n(2001 b) \mathrm{m}$ <br> and a set of nority, pove | odel included time dummy ty, hosVote | d the variables district |


| mooney Coeff. <br> Std. Err | Results after using Bayesian Model Averaging Techniques over 512 Models (Time modeled as a trend variable) |  |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | intercept | fem | relig | trend | md | piecemd | nvallag | holbrook | elindex | rosenstn | pcpi | urban | savage |
|  | -9.172 | 0.189 | -0.069 | -0.671 | 0.000 | -0.084 | 1.090 | 0.000 | 0.000 | -0.002 | 0.000 | 0.000 | -0.004 |
|  | 3.181 | 0.076 | 0.037 | 0.423 | 0.000 | 0.060 | 0.447 | 0.000 | 0.000 | 0.002 | 0.000 | 0.001 | 0.032 |
| Results after using Bayesian Model Averaging Techniques over 512 Models (Time modeled as a year-specific dummies) ${ }^{\text {a }}$ |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | intercept | fem | relig | trend |  | piecemd | nvallag | holbrook | elindex | rosenstn | pcpi | urban | savage |
| Coeff. | -10.580 | 0.153 | -0.058 |  | 0.000 | -0.011 | 1.477 | -3.59E-18 | -7.97E-12 | 0.000 | -3.61E-09 | 4.54E-05 | 0.004 |
| Std. Err. | 3.191 | 0.074 | 0.035 |  | 0.000 | 0.014 | 0.558 | $2.11 \mathrm{E}-18$ | 3.96E-12 | 0.001 | $3.07 \mathrm{E}-09$ | $1.24 \mathrm{E}-04$ | 0.064 |
|  |  |  |  |  | ults from | Mooney | Lee' | Original | del $1{ }^{\text {b }}$ |  |  |  |  |
|  | intercept | fem | relig | trend | MD | piecemd | nvallag | holbrook | elindex | rosenston | ne pcpi | urban | savage |
| Coeff. | -2.714 | - | - | -. 870 | - | - |  | - |  | -. 363 | . 001 | -. 008 | -. 389 |
| Std. Err. | 2.219 | - | - | . 367 | - | - | - | - |  | . 354 | . 001 | . 021 | 1.035 |
| Results from Mooney and Lee's Original Model $2{ }^{\text {b }}$ |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | intercept | fem | relig | Trend | MD | piecemd | nvallag | holbrook | elindex | rosenston | ne pcpi | urban | savage |
| Coeff. | -6.936 | . 222 | -. 102 | -1.225 | . 017 | -. 221 | . 866 | -. 074 | -. 620 | - | - | - | - |
| Std. Err. | 3.851 | . 088 | . 044 | . 566 | . 009 | . 112 | . 511 | . 031 | . 310 | - | - | - | - |
| NOTES: Significant results (with $95 \%$ confidence or better) are in bold. ${ }^{\text {a. }}$ None of the year-specific time dummies were significant and for space reasons, they are not reported here. The results are available upon request from the author. ${ }^{\text {b }}$. Mooney and Lee (1995) estimate two different models. The first model is called the "No-Effects" model and only includes the "usual suspects:" rosenstone, pcpi, urban, savage, and trend. The second model includes fem, relig, md, piecemd, nvallag, holbrook, elindex, and trend. See Table 1 in this paper for variable definitions. |  |  |  |  |  |  |  |  |  |  |  |  |  |


| Results after using Bayesian Model Averaging Techniques over 512 Models (Time modeled as year-specific dummies) |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | intercpt | dum1989 | dum1990 | dum199 | dum1992 | union | priv | starevpc | seidiff | reform80 | elect | repleg | govr1 | diffuse | entre | entresc |
| Coeff. | -4.007 | 3.161 | 3.177 | 2.158 | 3.841 | -0.748 | 0.072 | 0.001 | 0.000 | 0.004 | 0.000 | -0.009 | 0.003 | 0.032 | 0.005 | 0.000 |
| Std. Err. | 0.978 | 0.792 | 0.813 | 0.942 | 0.876 | 0.709 | 0.051 | 0.001 | 0.012 | 0.009 | 0.000 | 0.037 | 0.220 | 0.013 | 0.002 | 0.000 |
| Results after using Bayesian Model Averaging Techniques over 512 Models (Time modeled as trend variable) |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | intercp |  | Time d | mmies re end varia | $\begin{aligned} & \text { laced by } \\ & \text { le } \end{aligned}$ | union | priv | starevpc | seidiff | reform80 | elect | repleg | govr1 | diffuse | entre | entresc |
| Coeff. | -3.813 | 1.626 | - | - | - | -0.790 | 0.066 | 0.001 | 0.001 | 0.004 | -0.001 | -0.002 | 0.009 | 0.013 | 0.004 | 0.000 |
| Std. Err. | 0.886 | 0.377 | - | - | - | 0.670 | 0.049 | 0.001 | 0.001 | 0.011 | 0.000 | 0.037 | 0.037 | 0.004 | 0.002 | 0.000 |
| Results from Mintrom's Original Model C2: Entrepreneur Present ${ }^{\text {a }}$ |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | intercpt | dm1989 | dm1990 | dm1991 | dm1992 | union | priv | starevpc | seidiff | reform80 | elect | repleg | govr1 | diffuse | entre | Entresc |
| Coeff. | -5.126 | 1.720 | 2.864 | 0.345 | 3.858 | -1.307 | 0.111 | 0.022 | 0.300 | -0.011 | -1.931 | 0.897 | -0.032 | 2.053 | 1.630 | - |
| Std. Err. | 1.662 | 0.906 | 1.158 | 1.187 | 1.374 | 0.820 | 0.067 | 0.019 | 0.221 | 0.202 | 0.832 | 0.767 | 0.492 | 1.017 | 0.551 | - |
| Results from Mintrom's Original Model C2: Entrepreneur Score |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | intercpt | dm1989 | dm1990 | dm1991 | dm1992 | union | priv | starevpc | seidiff | reform80 | elect | repleg | govr1 | diffuse | ntre | ntresc |
| Coeff. | -5.807 | 1.710 | 3.012 | 0.648 | 4.395 | -1.149 | 0.113 | 0.029 | 0.386 | -0.068 | -2.013 | 1.038 | 0.079 | 2.033 | - | 0.050 |
| Std. Err. | 1.767 | 0.927 | 1.184 | 1.192 | 1.424 | 0.851 | 0.069 | 0.019 | 0.231 | 0.210 | 0.853 | 0.779 | 0.508 | 1.046 | - | 0.013 |
| NOTES: Significant results (with 95\% confidence or better) are in bold. Results from Mintrom's original models are reproduced from Mintrom (1997), "Table 2. Models of Initial State Legislative Consideration of School Choice," page 757. See Mintrom (1997) for further discussion of these original results. All models are for legislative consideration of school choice. Mintrom also includes a set of models for adoption, but those models are not considered here. ${ }^{\text {a. Mintrom also includes a }}$ model C1: Baseline, but those results are not reported here as the baseline model does not include either the entrepreneur or entrepreneur's activity score variables. See Table 1 in this paper for variable definitions. |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |


| Results after using Bayesian Model Averaging Techniques over 32 Models (With PARTY, Time introduced as trend variable) |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | intercept | elect1 | elect2 | income | fiscal | party | religion | neighbor | trend |
| Coeff. | -4.145 | 0.250 | 0.126 | 0.016 | -1.596 | -0.183 | -0.028 | 0.237 | 0.185 |
| Std. Err. | 0.713 | 0.117 | 0.130 | 0.008 | 0.681 | 0.093 | 0.010 | 0.093 | 0.135 |
| Results after using Bayesian Model Averaging Techniques over 16 Models (Without PARTY, Time introduced as trend variable) |  |  |  |  |  |  |  |  |  |
|  | intercept | elect1 | elect2 | income | fiscal | party | religion | neighbor | trend |
| Coeff. | -4.218 | 0.250 | 0.125 | 0.016 | -1.653 | - | -0.027 | 0.231 | 0.177 |
| Std. Err. | 0.705 | 0.116 | 0.129 | 0.008 | 0.681 | - | 0.010 | 0.092 | 0.133 |
| Results from Berry \& Berry's Original Model (1): With PARTY |  |  |  |  |  |  |  |  |  |
|  | intercept | elect1 | elect2 | income | fiscal | party | religion | neighbors | trend |
| Coeff. | -4.51 | 0.82 | 0.59 | 0.023 | -1.69 | -0.4 | -0.034 | 0.27 | - |
| T-ratio | -5.46 | 2.34 | 1.71 | 3.34 | -1.3 | -1.83 | -2.11 | 2.86 | - |
| Results from Berry \& Berry's Original Model (2): Without PARTY |  |  |  |  |  |  |  |  |  |
|  | intercept | elect1 | elect2 | income | fiscal | party | religion | neighbors | trend |
| Coeff. | -4.62 | 0.79 | 0.56 | 0.23 | -1.82 | - | -0.035 | 0.25 | - |
| T-ratio | -5.64 | 2.31 | 1.68 | 3.33 | -1.44 | - | -2.23 | 2.78 | - |

NOTES: Significant results (with 95\% confidence or better) are in bold. Results from Berry \& Berry's (1990) original models are reproduced from "Table 1. Probit Maximum Likelihood Estimates for Event History Analysis Model of Lottery Adoption" page 406. The original table reported t-ratios instead of standard errors, so the t-ratio is presented here as well. See Berry \& Berry (1990) for further discussion of these original results. See Table 1 in this paper for variable definitions.

| Results after using Bayesian Model Averaging Techniques over 32 Models (With FISCAL, Time introduced as trend variable) |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | intercept | incomeRel | urban | fiscal | elect1 | elect2 | previoiusad | ideology | trend |
| Coeff. | -1.195 | -1.018 | 0.006 | -0.485 | -0.233 | 0.479 | 0.075 | -0.577 | -0.034 |
| Std. Err. | 0.481 | 0.594 | 0.004 | 0.165 | 0.155 | 0.176 | 0.128 | 0.359 | 0.101 |
| Results from Berry \& Berry's Original Model (1): With FISCAL |  |  |  |  |  |  |  |  |  |
|  | intercept | incomeRel | urban | fiscal | elect1 | elect2 | previoiusad | ideology | trend |
| Coeff. | -0.92 | -1.8 | 0.0165 | -1.21 | -0.93 | -0.63 | 0.019 | 0.79 | - |
| T-ratio | -1.82 | -2.02 | 1.5 | -1.51 | -3.07 | -1.84 | 0.15 | 2.47 | - |
| Results after using Bayesian Model Averaging Techniques over 16 Models (Without FISCAL, Time introduced as trend variable) |  |  |  |  |  |  |  |  |  |
|  | intercept | incomeRel | urban | fiscal | elect1 | elect2 | previoiusad | ideology | trend |
| Coeff. | -1.345 | -0.976 | 0.004 | - | -0.468 | -0.123 | 0.107 | 0.296 | 0.042 |
| Std. Err. | 0.387 | 0.473 | 0.004 | - | 0.144 | 0.113 | 0.090 | 0.135 | 0.090 |
| Results from Berry \& Berry's Original Model (2): Without FISCAL |  |  |  |  |  |  |  |  |  |
|  | intercept | incomeRel | urban | fiscal | elect1 | elect2 | previoiusad | ideology | trend |
| Coeff. | -1.02 | -1.55 | 0.0126 | - | -0.085 | -0.034 | 0.119 | 0.58 | - |
| T-ratio | -2.74 | -2.31 | 1.43 | - | -3.38 | -1.44 | 1.47 | 2.38 | - |

NOTES: Significant results (with 95\% confidence or better) are in bold. Results from Berry \& Berry's (1992) original models are reproduced from "Table 1. Probit Maximum Likelihood Estimates for Event History Analysis of Tax Adoption" page 730. The original table reported t-ratios instead of standard errors, so the tratio is presented here as well. See Berry \& Berry (1992) for further discussion of these original results. See Table 1 in this paper for variable definitions.

| Results after using Bayesian Model Averaging Techniques over 32 Models (With FISCAL, Time introduced as trend variable) |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | intercept | incomerel | urban | fiscal | elect1 | elect2 | previoiusad | cars | trend |
| Coeff. | -0.579 | -1.348 | -0.002 | -0.594 | -0.082 | 1.698 | 0.153 | -0.095 | 0.565 |
| Std. Err. | 0.496 | 0.485 | 0.004 | 0.127 | 0.150 | 1.417 | 0.115 | 0.383 | 0.239 |
| Results from Berry \& Berry's Original Model (3): With FISCAL |  |  |  |  |  |  |  |  |  |
|  | intercept | incomerel | urban | fiscal | elect1 | elect2 | previoiusad | cars | trend |
| Coeff. | 0.09 | -1.65 | -0.0033 | -0.23 | -1.81 | -0.55 | 0.4 | 6.57 | - |
| T-ratio | 0.14 | -2.95 | -0.4 | -0.29 | -4.57 | -1.59 | 3.84 | 2.26 | - |
| Results after using Bayesian Model Averaging Techniques over 16 Models (Without FISCAL, Time introduced as trend variable) |  |  |  |  |  |  |  |  |  |
|  | intercept | incomerel | urban | fiscal | elect1 | elect2 | previoiusad | cars | trend |
| Coeff. | -0.572 | -1.294 | -0.002 | - | -0.614 | -0.056 | 0.110 | 0.838 | 0.644 |
| Std. Err. | 0.425 | 0.405 | 0.003 |  | 0.124 | 0.126 | 0.101 | 1.236 | 0.215 |
| Results from Berry \& Berry's Original Model (4): Without FISCAL |  |  |  |  |  |  |  |  |  |
|  | intercept | incomerel | urban | fiscal | elect1 | elect2 | previoiusad | cars | trend |
| Coeff. | 0.08 | -1.41 | 0.0022 | - | -1.75 | -0.4 | 0.36 | 4.67 | - |
| T-ratio | 0.17 | -3.11 | -0.35 | - | -4.86 | -1.45 | 0.65 | 0.52 | - |


| Table 8c. Summary of BMA Results of EHA of state any tax adoption, 1919-39; 1960-71 (Berry \& Berry 1992), 16 \& 32 models with uniform model priors |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Results after using Bayesian Model Averaging Techniques over 32 Models (Any Tax, 1919-39, With FISCAL, Time introduced as trend variable) |  |  |  |  |  |  |  |  |  |
|  | intercept | incomerel | urban | fiscal | elect1 | elect2 | recentad | ideology | trend |
| Coeff. | -1.120 | 0.054 | 0.003 | -0.726 | -0.236 | 0.067 | -0.039 | -0.365 | -0.026 |
| Std. Err. | 0.264 | 0.294 | 0.003 | 0.116 | 0.081 | 0.112 | 0.071 | 0.170 | 0.057 |
| Results from Berry \& Berry's Original Model (5): With FISCAL |  |  |  |  |  |  |  |  |  |
|  | intercept | incomerel | urban | fiscal | elect1 | elect2 | recentad | ideology | trend |
| Coeff. | -1.01 | -0.16 | 0.0081 | -0.84 | -1.44 | -0.69 | 0.049 | 0.12 | - |
| T-ratio | -4.49 | -0.41 | 1.43 | -2.39 | -6.66 | -4.03 | 0.65 | 0.52 | - |
| Results after using Bayesian Model Averaging Techniques over 16 Models (Any Tax 1919-39, Without FISCAL, Time introduced as trend variable) |  |  |  |  |  |  |  |  |  |
|  | intercept | incomerel | urban | fiscal | elect1 | elect2 | recentad | ideology | trend |
| Coeff. | -0.930 | -0.181 | 0.002 | - | -0.690 | -0.164 | 0.069 | 0.115 | -0.010 |
| Std. Err. | 0.212 | 0.234 | 0.002 |  | 0.086 | 0.064 | 0.035 | 0.079 | 0.046 |
| Results from Berry \& Berry's Original Model (6): Without FISCAL |  |  |  |  |  |  |  |  |  |
|  | intercept | incomerel | urban | fiscal | elect1 | elect2 | recentad | ideology | trend |
| Coeff. | -0.77 | -0.37 | 0.0061 | - | -1.34 | -0.51 | 0.114 | 0.17 | - |
| T-ratio | -4.31 | -1.2 | 1.33 | - | -8.16 | -3.96 | 3.11 | 1.11 | - |
| Results after using Bayesian Model Averaging Techniques over 32 Models (Any Tax 1960-71, Time introduced as trend variable) |  |  |  |  |  |  |  |  |  |
|  | intercept | incomecon | urban | fiscal | elect1 | elect2 | recentad | instit | trend |
| Coeff. | -2.542 | 0.004 | -0.001 | -0.435 | -0.042 | 0.148 | 0.085 | -1.645 | 0.144 |
| T-ratio | 0.587 | 0.006 | 0.003 | 0.149 | 0.100 | 0.104 | 0.138 | 0.584 | 0.131 |
| Results from Berry \& Berry's Original Model (7): Any Tax, 1960-71 |  |  |  |  |  |  |  |  |  |
|  | intercept | incomecon | urban | fiscal | elect1 | elect2 | recentad | instit | trend |
| Coeff. | -2.58 | 0.0096 | -0.0037 | -2.87 | -1.06 | -0.31 | 0.149 | 0.29 | - |
| T-ratio | -3.8 | 1.58 | -0.55 | -2.56 | -3.1 | -1.45 | 1.02 | 1.34 | - |
| NOTES: Significant results (with $95 \%$ confidence or better) are in bold. Results from Berry \& Berry's (1992) original models are reproduced from "Table 1. Probit Maximum Likelihood Estimates for Event History Analysis of Tax Adoption" page 730. The original table reported t-ratios instead of standard errors, so the tratio is presented here as well. See Berry \& Berry (1992) for further discussion of these original results. See Table 1 in this paper for variable definitions. |  |  |  |  |  |  |  |  |  |


[^0]:    * The author would like to thank Jasjeet Sekhon for very useful advice and comments. Thanks also to Michael Mintrom, Chris Mooney, Kenneth Wong, and William D. Berry for making their data available for re-analysis. All errors are my own.

[^1]:    ${ }^{1}$ Bartels (1997) cites the work of Draper (1995) and Raftery (1995) as developers of the technique, and he also acknowledges Jeffreys (1961) and Leamer (1978) as building blocks for the technique.
    ${ }^{2}$ Data sets from the Mintrom (1997) and Mooney and Lee (1995) studies were provided, on request, by the original authors. Data sets from the Berry \& Berry $(1990,1992)$ studies were obtained from the author's web site: http://www.fsu.edu/\%7Epolisci/berry/a.html.Two other data sets are not considered here: Mintrom and Vergari (1998) and Hays and Glick (1997). The Mintrom and Vergari (1998) data is not analyzed because it is quite similar to the Mintrom (1997) data set. The Hays and Glick (1997) data set is not used because the data is currently unavailable from the authors (Personal communication with Scott Hays, January 2002).

[^2]:    ${ }^{3}$ It should also be noted that identifying and measuring the dependent variable may not be straightforward either. Although the passing of a law is one indicator of policy adoption, all laws are not equal. In addition, passing a law may not necessarily lead to implementation of the policy. These two issues are discussed in the paper's section on the state of research methodology in the state policy innovation literature.

[^3]:    ${ }^{4}$ Event history analysis, also called hazard or proportional-hazard models, were used in many other areas before being picked up by political scientists. For further discussion on the history and application of EHA in the social sciences, readers are encouraged to see Allison (1984) and Yamaguchi (1991).
    ${ }^{5}$ A prevalent suggestion for improvement in state policy research is the call echoed by Mooney (2001) for renewed focus on micro-level processes, e.g. individual state lawmakers.

[^4]:    ${ }^{6}$ In a recent paper on the international diffusion of "gender mainstreaming" organizations, True and Mintrom (2001) address this problem by running both an EHA model and a second logit model that identifies "high-level" vs. "low-level" mechanisms of gender mainstreaming. This approach may also be useful in state policy innovation research.

[^5]:    ${ }^{7}$ As another example, Berry and Berry (1990) write about the attractiveness of a "conception of regional [that] would involve both predesignated regions and predesignated leader states within those regions ... this conception of regional diffusion is most attractive when there are reliable data about which states are

[^6]:    ${ }^{9}$ The debate was sparked by Lott and Mustard's (1997) controversial finding that concealed-weapons laws deterred violent crimes without increasing accidental deaths. Critics such as Black and Nagin (1998) and Dezhbakhsh and Rubin (1998) were quick to attack the model specification used by Lott and Mustard. Lott (1998) responded, but the debate remained unsettled. Bartley and Cohen (1998) estimated the model uncertainty in Lott and Mustard's specification by using an extreme bound analysis. This extreme bound analysis is based on the same principle as BMA: instead of relying on one "best" model, run a bunch of models (nearly 20,000 in the case of Bartley and Cohen) to see how robust the finding is.

[^7]:    ${ }^{10}$ Bartels (1997) provides a formal discussion of BMA and discusses the assumptions underlying the models.

[^8]:    ${ }^{11}$ Equations [1] and [2] here correspond to Bartels (1997) equations [5] and [6]. They are derived from an earlier set of equations in Bartels' article. See Bartels (1997) for this discussion.
    ${ }_{13}^{12}$ Equation [3] corresponds to Bartels (1997) equation [9], which is derived in the Bartels article.
    ${ }^{13}$ In statistical programs such as R, the BIC() command computes the BIC directly. It can also be derived from the Mean Square Error (MSE) by: BIC $=n \ln (\mathrm{MSE})+k \ln (n)$, where $n$ is the number of observations and $k$ is the number of parameters being estimated.
    ${ }^{14}$ Equation [5] here corresponds to Bartels equation [16]. Bartels notes that this solution is arrived at by repeatedly applying the derived equation [12]: $\pi_{\mathrm{i}} / \pi_{\mathrm{j}}=B_{\mathrm{ij}} \pi_{\mathrm{i}}^{0} / \pi_{\mathrm{j}}^{0}$, where $\pi_{\mathrm{i}}^{0}$ and $\pi_{\mathrm{j}}^{0}$ are the prior model odds.
    ${ }^{15}$ Bartels (1997) shows how this can be done when he discusses dummy-resistant model priors in the context of BMA analysis of Lange and Garrett $(1985,1987)$ and Jackman (1987).

[^9]:    ${ }^{16}$ Explanations of charter school variables will be kept brief in this paper. For a more thorough explanation of these and other variables, readers can see Wong and Shen (2001b) and the long list of references cited

[^10]:    therein.
    ${ }^{17}$ An alternative argument is that high levels of private school activity would actually reduce the incentive for charter schools to operate because there are already a number of options available for dissatisfied public school parents and students. The costs of private schools, however, cast doubt on this hypothesis. One of the reasons charter schools are attractive to parents is that they resemble private school environments (small, focused communities), but require no additional tuition.
    ${ }^{18}$ This variable was constructed in two steps. First, census (current population survey) data provided the total number of school-aged (ages 5-17) students in each state. Then, NCES data provided the total public school enrollment in each state. The ratio of public school enrollment over all eligible students gave the \% enrolled in public schools, and this number was then subtracted from 1 to produce the "percentage of student-aged population not enrolled in public schools." The hypothesis is that those student-aged children not enrolled in public schools are in private educational alternatives. One potential confounding factor is the high school drop out rate, but when this was factored into the formula, a number of states had enrollments greater than $100 \%$ in public schools, thus making the data incompatible. Further, many students who are "dropouts" in reality (i.e. not attending school) may still be officially enrolled in their public school system. This may help to make this proxy more accurate.

[^11]:    ${ }^{19}$ Exploratory analysis also employed the series of time dummies, as used in Wong and Shen (2001) and Mintrom (1997). These models had significantly less explanatory power than the exact same models in which the time trend variable was used instead.
    ${ }^{20}$ Again, a more thorough discussion is available in Wong and Shen (2001).

[^12]:    ${ }^{21}$ Texas Open-Enrollment Charter Schools: Third Year Evaluation, 1998-99. Available on-line at: http://www.tea.state.tx.us/charter/.

[^13]:    ${ }^{22}$ The party control index (ran4yr) is a 4-year lagged Ranney party competition index. An alternative measure is the 8 -year lagged index (ran8yr), but as shown in Wong and Shen (2001) the two measures are virtually interchangable when included in charter school law adoption models.
    ${ }^{23}$ The same can be said about population. Wong and Shen (2001) include state population in their analysis of charter school adoption. It was not a useful explanatory variable in their models and is thus not considered further here.

[^14]:    ${ }^{24}$ These preliminary tests were run using the statistical package R , and the R -code is available for review on the Internet at: http://www.people.fas.harvard.edu/~fxshen/data/.
    ${ }^{25}$ Note Bartels and Zaller's (2001) heading, "Forty-eight models are better than one" (p.10) and Erikson, Bafumi, and Wilson's (2001) reply that, "Ninety-six models are better than forty-eight" (p. 815).

[^15]:    ${ }^{26}$ It might be argued that other variables should be designated the "essential" variables, and if it was decided that in fact other variables should be designated as essential, an alternative round of analyses could be carried out.
    ${ }^{27}$ Year-specific dummies were introduced for the years 1966-1971.

[^16]:    ${ }^{28}$ Berry and Berry (1990), p. 404.
    ${ }^{29}$ In the models where the fiscal variable was not included, there are only 16 models considered.

[^17]:    ${ }^{30}$ Berry \& Berry (1990), p. 401.

[^18]:    ${ }^{31}$ Berry \& Berry (1992), p. 728.
    ${ }^{32}$ BMA can also be extended and made more sophisticated. Dropping the assumption of uniform model priors, and assigning prior probabilities based on relevant theory is one obvious avenue for more additional analysis.

[^19]:    ${ }^{33}$ In the case of state policy innovation, a "data-driven" approach to choosing variables seems illogical, as the motivations for the study in the first place are usually theory-driven, e.g. "I think that political factors affect policy adoption." Although data-driven approaches such as the "Occam's Window" approach advanced by Hoeting, et. al. (1999) are more formal, they would translate into the researcher saying, "I have little idea about what variables affect state policy innovation, but I have a lot of state-level variables, so I'll just let the data decide what variables are most important." This is not what any state policy innovation researcher says before carrying out their study.

