Bayesian Models to Predict the Return to Prison

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Abstract

The United States has the highest prison incarceration rate among the developed countries in the world. The shares of state budgets devoted to departments of corrections have grown substantially with the ever-growing prison population. About half of all persons in the United States who are released from prison return within three years. This high recidivism rate contributes to the budgetary difficulties faced by many states with respect to the costs of crime and incarceration. Three Bayesian statistical methods are applied to a rich Utah dataset covering release and return over a period of three years in our research. We explore criminological, sociological, and economic factors to predict parolees' returns to prison. Using reasonable classes of priors, the model results based on Extreme Bounds Analysis, Bayesian Model Averaging, and Bayesian Classification and Regression Trees are compared in order to provide useful public policy guides.

Key Words: Bayesian, model selection, model averaging, recidivism

1. Background

Growth of the prison population in the United States has exploded over the last 30 years. Largely due to changes in laws relating to mandatory minimum sentencing and increasingly stringent attitudes toward "being tough on crime," the U.S. currently incarcerates 754 persons per 100,000 residents (Sabol, West, and Cooper, 2009). The extreme magnitude of the U.S. incarceration rate can be appreciated by comparing it with countries at a similar socio-economic level of development. In 2003, the incarceration rate averaged across Australia, Austria, Canada, Denmark, England and Wales, Finland, France, Germany, Iceland, Ireland, the Netherlands, New Zealand, Northern Ireland, Scotland, Sweden, and Switzerland was approximately 95 persons per 100,000 citizen, while the U.S. incarcerated 715 per 100,000 in that same year (Aebi et al., 2006; Harrison and Karberg, 2004; New Zealand Department of Corrections, 2004; United Nations, 2007).

Despite the striking differences in incarceration rates, U.S. crime rates are not much different from the crime rates found in these 16 counties, nor are there substantial differences in recidivism rates. The crime rate for serious crimes (i.e., intentional homicide, assault, rape, robbery, and theft) in the U.S. was 5,018 crimes per 100,000 citizens in 2003, whereas the average crime rate for the 16 aforementioned countries was 4,936 (Aebi et al., 2006; Federal Bureau of Investigation, 2004; New Zealand Police, 2004; United Nations, 2007). As for recidivism rates, Langan and Levin (2002) found that the United States' three-year return-to-prison rate was 51.8 percent, which falls roughly in the middle of the rates for European counties (see Wartna and Nijssen (2006) for references to European recidivism rates).

Return to prison, or recidivism, has always been an important research topic in its own right. Recently, because of the high U.S. incarceration rate and the burden

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placed on state budgets to house prisoners, it has become a policy issue of top priority, one in need of careful empirical research for its development. Most of the previous studies on recidivism have relied solely on data from state departments of corrections and have focused primarily on socio-demographic and criminological explanations of recidivism. Consistent with these types of explanations, the two predictors that have received the greatest attention are age at the time of release from prison and prior incarcerations. Age at the time of release from prison has been shown to exhibit a strong negative relationship with returns to prison consistently throughout the literature (Bales and Mears, 2008; Beck and Shipley, 1989; Chiricos, Barrick, Bales, and Bontrager, 2007; Gendreau, Little, and Goggin, 1996; Langan and Levin, 2002). Virtually all previous research has demonstrated a very strong positive relationship between the number of prior incarcerations and recidivism (Bales and Mears, 2008; Beck and Shipley, 1989; Chiricos et al., 2007; Gendreau et al., 1996; Langan and Levin, 2002; Pritchard, 1979).

In this paper we utilize a rich socio-economic data set that allows us to explore different types of models to predict the return to prison. Recognizing that there is fundamental uncertainty regarding model selection and model parameters, we utilize three Bayesian approaches. The survey methodology and descriptive statistics are summarized in Section 2. Overviews and results for each of the three methodological approaches are provided in Section 3. Extreme Bounds Analysis (EBA) is introduced in Section 3.1, Bayesian Model Averaging (BMA) is described in Section 3.2, and Classification and Regression Trees (CART) modeling is presented in Section 3.3. In Section 4, these three approaches are compared. We conclude with a brief discussion of how our results might be usefully applied by decision makers in reducing the costs associated with recidivism in Section 5. Our results suggest that policy makers should strive to enhance employment opportunities for parolees through mechanisms such as tax credits to employers and post-release education programming for persons released from prison. Furthermore, we discover strong evidence that court-mandated fees, such as restitution payments and child support payments, increase considerably the probability that parolees will recidivate and states should consider alternatives to these explicit taxes on parolee earnings.

2. Data

Each month in Utah, all persons on parole have to report, in person, to the Utah Adult Probation and Parole Office. There is no systematic time of the month when the parolees are required to report. During the third week of May, 2006, all parolees reporting were provided a questionnaire. The questions were similar to those asked in the U.S. Current Population Survey regarding employment, earnings, housing, and living. With a nearly 100 percent response rate for one-quarter of the persons on parole, this survey was the foundation for the Utah Census of Parolees (2008).[1] Information from the survey was matched with data provided by the Utah State Department of Corrections. These data included information about criminal history and education. The Utah State Department of Corrections provided an update in May, 2009 that allowed us to tabulate how many persons returned to prison along with the reason for return in each case. This new data is the basis of the research in this paper.

[1]The authors wish to thank Mr. Jeffrey R. Galli, Utah State Office of Education and former warden of the Utah State Prison, for his invaluable assistance in making these data available for our use.

Recidivism can be defined in many distinct ways. Here we define recidivism as any return to prison, which could include either a technical parole violation or the commission of a new crime. The set of variables we consider in this research to account for the return to prison indicator are comprised of traditional criminological variables including race, age, prior incarcerations, gender, and the type of crime committed by the offender that resulted in the most recent prison sentence. The novelty of this data set lies in its inclusion of a set of economic variables, a feature that is only rarely found within the recidivism literature. These economic variables include employment, earnings, occupational classification, and court-mandated payments for restitution and child support.

The variables are defined in Table 1. Descriptive statistics for the complete sample of 506 observations for which all information was available are provided in Table 2. In this sample, the three-year recidivism rate, measured by the *return* variable, is 43.68 percent. This value is consistent with Utah Department of Corrections values for the entire population.

3. Methodologies

While many statistical procedures are available to measure the extent to which explanatory variables influence the return to prison, this research examines three fundamentally Bayesian methods that can account for both model and parameter uncertainty. Mostly we stay with simple linear representations in order to highlight important relationships that can be readily understood. Our hope is that our results adequately translate to sensible policy recommendations. Section 3.1 provides an overview of EBA as introduced by Chamberlain and Leamer in a series of articles beginning in 1976 (Chamberlain and Leamer, 1976; Leamer, 1978; Leamer, 1982). The overview is followed by a summary of the EBA results. Section 3.2 looks at BMA, an approach developed by Raftery, Hoeting, and Volinksy (1997), and summarizes the results of a BMA model. Finally, Section 3.3 reviews the CART methodology as introduced by Breiman, Friedman, Olshen, and Stone (1984) and discusses the results of a CART model.

3.1 Extreme Bounds Analysis

3.1.1 Overview

Based on a simple Bayesian linear model with a normal-gamma prior, EBA reveals the maximum and minimum values for the posterior means for the model slope parameters. EBA is a method of global sensitivity analysis that can take advantage of proper prior specifications for variables associated with subsets of possible variables to include in a regression specification. A nice twist on proper prior specification is to set the prior mean equal to zero for selected variables. These are called doubtful variables and would plausibly be dropped from any given specification. Dropping a variable is equivalent to a proper prior centered at zero with perfect precision. In calculating extreme posterior means, the bounds associated with the set of doubtful variables necessarily include zero. Specification of the prior variance/covariance is difficult and somewhat arbitrary. Therefore, EBA calculates posterior limits that correspond with a scalar value multiplied by a prior variance/covariance matrix. This scalar is swept from zero to infinity. Variables that are not properly specified are called free variables and are not associated with a prior specification. Nonetheless, extreme values for the posterior means for the free variables are calculated

Table 1: Definition of Variables

Variable Name	Variable Definition
return	Indicator variable for return to prison
age	Age at time of survey in May 2006
gender	Indicator variable, where 1=male and 0=female
priorinc	The number of prior incarcerations
racewh	Race/ethnicity indicator for White
racehi	Race/ethnicity indicator for Hispanic
racepi	Race/ethnicity indicator for Pacific Islander
racena	Race/ethnicity indicator for Native American
raceas	Race/ethnicity indicator for Asian
raceaa	Race/ethnicity indicator for African-American
drug	Indicator for most recent crime being drug offense
driving	Indicator for most recent crime being driving offense (DUI)
murder	Indicator for most recent crime being intentional homicide
othercrime	Indicator for most recent crime being unclassified
person	Indicator for most recent crime being against a person
property	Indicator for most recent crime being property offense
sexcrime	Indicator for most recent crime being sex-related offense
weapons	Indicator for most recent crime being weapons-related offense
hsdeg	Indicator variable for high school graduates
ged	Indicator variable for GED
colldeg	Indicator variable for college graduates
voccert	Indicator variable for vocational certificate
pednone	Indicator for no prison education
pedged	Indicator for prison education toward GED
pedhs	Indicator for prison education toward high school diploma
pedcuv	Indicator for prison education toward college/vocation
employed	Indicator variable for employment status
hrsweek	Number of hours worked per week (if employed)
wage	Hourly wage (if employed)
healthben	Indicator variable for work-related health benefits
jobmanage	Indicator variable for management occupation
jobbuild	Indicator variable for building maintenance occupation
jobsales	Indicator variable for sales occupation
joboffice	Indicator variable for office occupation
jobconstr	Indicator variable for construction occupation
jobinstall	Indicator variable for installation occupation
jobprod	Indicator variable for production occupation
jobtrans	Indicator variable for transporation occupation
restitution	Indicator variable for the payment of restitution
childsup	Indicator variable for the payment of child support
owncar	Indicator variable for ownership of a car

Table 2: Descriptive Statistics

Variable	Mean	Standard Deviation	Min	Max
return	0.4368	0.4965	0	1
age	36.8709	10.4882	20.58	74.92
gender	0.8597	0.3477	0	1
priorinc	1.9783	1.4287	0	1
racewh	0.7332	0.4427	0	1
racehi	0.1522	0.3595	0	1
racepi	0.0237	0.1523	0	1
racena	0.0198	0.1393	0	1
raceas	0.0119	0.1084	0	1
raceaa	0.0593	0.2364	0	1
drug	0.2451	0.4305	0	1
driving	0.0613	0.2401	0	1
murder	0.0257	0.1584	0	1
othercrime	0.0178	0.1323	0	1
person	0.1660	0.3725	0	1
property	0.2727	0.4458	0	1
sexcrime	0.2016	0.4016	0	1
weapons	0.0099	0.0990	0	1
hsdeg	0.7055	0.4563	0	1
ged	0.3597	0.4804	0	1
colldeg	0.0909	0.2878	0	1
voccert	0.2055	0.4045	0	1
pednone	0.2688	0.4438	0	1
pedged	0.2273	0.4195	0	1
pedhs	0.5020	0.5005	0	1
pedcuv	0.2984	0.4580	0	1
employed	0.7569	0.4294	0	1
hrsweek	29.8547	18.8288	0	84
wage	8.0745	5.7717	0	47
healthben	0.2609	0.4395	0	1
jobmanage	0.0455	0.2085	0	1
jobbuild	0.0375	0.1903	0	1
jobsales	0.0731	0.2606	0	1
joboffice	0.1067	0.3091	0	1
jobconstr	0.3024	0.4597	0	1
jobinstall	0.1047	0.3065	0	1
jobprod	0.1166	0.3213	0	1
jobtrans	0.0692	0.2540	0	1
restitution	0.5040	0.5005	0	1
childsup	0.3340	0.4721	0	1
owncar	0.4150	0.4932	0	1

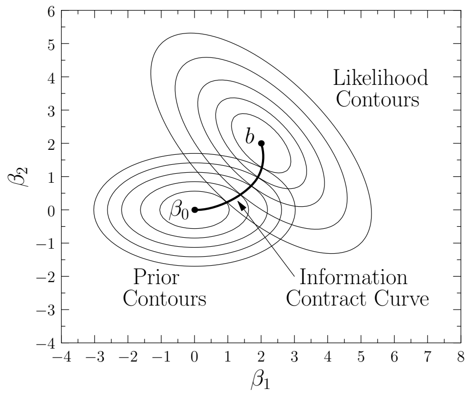

Figure 1: Likelihood/Prior Contours and Information Contract Curve.

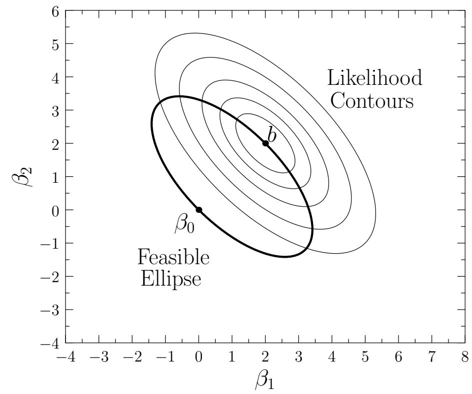

Figure 2: Feasible Ellipse.

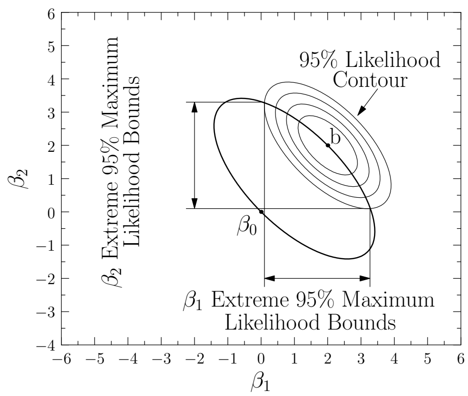

Figure 3: Extreme Bounds Within 95% Likelihood Contour.

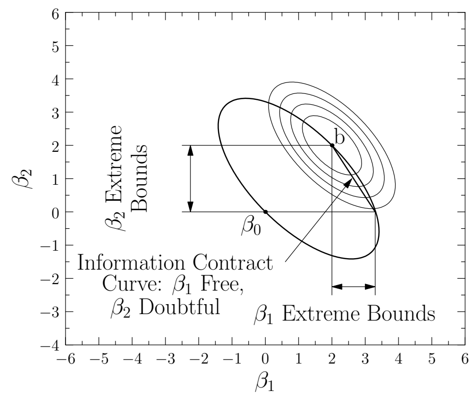

Figure 4: Information Contract Curve.

by EBA (see Chamberlain and Leamer (1976) for details). With a large number of possible explanatory variables there is an exponentially large number of possible doubtful/free combinations. In this paper, we pay attention to two reasonable specifications. Our "criminology prior" allows age and the number of prior incarcerations to be free. The remaining variables are set as doubtful. Our "economic prior" allows employment, health benefits, and court-mandated payments (restitution and child support) to be free and the remaining variables set as doubtful.

The potential set of posterior means can be graphically represented. In Figure 1, we illustrate the information contract curve as the locus of tangencies between iso-likelihood and iso-prior-probability contours. In this diagram, a fully specified prior is assumed and the posterior mean must fall along this curve.

By varying the prior variance/covariance matrix this curve changes, but a convex set that contains all possible information contract curves can be calculated. This is called the feasible ellipse and is illustrated in Figure 2. Given this information, the extreme bounds can be represented graphically as in Figure 3.

In Figures 1 through 3, both explanatory variables are doubtful. If we only set one variable as doubtful we can illustrate the bounds obtained in Figure 4. Here, the coefficient on the first explanatory variable is free (an improper prior).

Table 3: EBA Bounds for the Criminology and Economic Priors

Criminology Prior		
Variable	Lower Bound	Upper Bound
age	-0.0124	-0.0012
priorinc	0.0267	0.0746
Economic Prior		
Variable	Lower Bound	Upper Bound
employed	-0.47339	0.17417
hrsweek	-0.00503	0.00129
wage	-0.00977	0.01609
healthben	-0.09093	0.02526
restitution	0.03082	0.19417
childsup	0.05217	0.16144

3.1.2 Results

As noted above in Section 3.1.1, EBA can take advantage of splitting the set of explanatory variables into two classes: doubtful variables and free variables. The set of doubtful variables has fully specified priors in the normal-gamma conjugate class. All means are set to zero and the variance/covariance matrix is set to the identity matrix and is multiplied by a scalar which is swept from zero to infinity. The remaining free variables have no prior (diffuse). EBA output shows extremes for all variables, doubtful and free. There are 506 complete observations associated with 39 explanatory variables, which implies approximately 500 billion possible regressions (or possible free/doubtful splits). Our first specification we call the "criminology prior." In this prior, we focus attention on the two most widely accepted variables as mentioned in Section 1 to be free: age and the number of prior incarcerations. A constant term is also included as a free variable. The remaining 36 variables are treated as doubtful. Because the extreme bounds for doubtful variables always cover zero and are, therefore, fragile, we only report the results in Table 3 for the free variables, *priorinc* and *age*.

Table 3 reveals that both age and the number of prior incarcerations are non-fragile; the lower and upper bounds do not cover zero. These results conform to previous research conducted using traditional methods.

Because there are fewer published studies that examine the economic effects of recidivism, we selected a broader list of 7 free variables to consider here. In Table 3, we report six EBA bounds for employment, the number of hours worked per week, hourly wage, whether the parolee received health benefits, whether the parolee paid restitution, and whether the parolee paid child support. A constant term was also added as a free variable. The remaining 32 variables were set as doubtful.

These results show that only the court mandated variables are non-fragile: whether or not the parolee is required to pay restitution or child support. Both elevate the probability of return to prison. Surprisingly, employment is fragile in the sense that of the nearly 500 billion models that could be constructed there are some specifications that would discover posterior means showing being employed increases the likelihood of returning to prison. Whether or not these types of models themselves have high posterior probabilities is considered in the next section.

3.2 Bayesian Model Averaging

3.2.1 Overview

Although EBA provides insight as to the range of possible values of posterior means for very rich sets of models, it does not pay direct attention to the posterior probabilities of the corresponding models. It is possible, for instance, to discover fragility corresponding with implausibility as measured in terms of likelihood. In this section, we address the issue of model posterior probability via Bayesian Model Averaging as developed in Raftery, Madigan, and Hoeting (1997) following a suggestion by Leamer (1978). Because a "true" model is not known (or even knowable) inferences about any particular model's parameters are troubling.

Uncertainty over model choice in our paper is related to the choice of variables to be included in a regression. Indeed, as noted by Bradley Efron, the choice of what variables to include in a regression model is one of the most challenging statistical problems today. Model selection is related to model likelihood via goodness of fit and to a preference for model parsimony. In particular, we chose to use the Bayesian Information Criterion (BIC) as presented in Schwarz (1978) with minimally specified (or diffuse) reference priors. The BIC score approximates the integrated likelihood of a model that is a paramount feature in model comparison.

The *bicreg* procedure in the computer package R uses an efficient branch and bound algorithm to find sets of models that have high posterior probabilities. These sets of models have differing parameters. Basically, a BMA "estimate" is a weighted average over models, where the weights correspond to model likelihood. Because the number of models is large, BMA also provides, for each variable, a probability of exclusion over the model space. We tend to think that if a variable is always excluded, it is not relevant in terms of policy decision making. In this paper, we allow BMA to choose among all possible variables and do not set up classes of proper priors as we did under EBA. As shown in Section 3.2.2, however, BMA results do align somewhat with EBA. The results show similarities to the extent that certain non-fragile variables (EBA) have high posterior probabilities of being included over the BMA model space.

3.2.2 Results

BMA model averages for a linear probability model using the same set of variables included in EBA are shown in Table 4. The table presents the variable, the posterior probability of the variable being included ($p! = 0$), and the average posterior mean and standard deviation for the top 5 models, ranked in terms of their posterior probabilities. Aside from the constant term, the number of prior incarcerations is a variable that appears in over 92 percent of models. The parolee's age is also highly favored. These two variables were non-fragile under EBA. Employment and the number of hours worked per week were also variables favored by BMA, but were fragile under EBA. The court-mandated, tax-like variables, restitution and child support, are often included.

An advantage of BMA is that it allows for the easy detection of the effects of collinearity. In Table 4, we see that when employment is included in a model, the

Table 4: Bayesian Model Averaging for Predicting Recidivism

	$p! = 0$	EV	SD	M_1	M_2	M_3	M_4	M_5
intercept	100.0	0.637	0.129	0.662	0.661	0.709	0.683	0.684
age	80.6	-0.005	0.003	-0.007	-0.007	-0.007	-0.007	-0.007
gender	0.0	0.0	0.0	·	·	·	·	·
priorinc	92.2	0.045	0.020	0.053	0.048	0.049	0.049	0.049
racehi	0.0	0.0	0.0	·	·	·	·	·
racepi	0.0	0.0	0.0	·	·	·	·	·
racena	0.0	0.0	0.0	·	·	·	·	·
raceas	51.6	-0.257	0.286	-0.518	·	-0.488	-0.476	·
raceaa	65.7	0.152	0.131	0.229	0.236	0.225	0.230	0.230
drug	0.0	0.0	0.0	·	·	·	·	·
driving	0.0	0.0	0.0	·	·	·	·	·
murder	0.0	0.0	0.0	·	·	·	·	·
othercrime	0.0	0.0	0.0	·	·	·	·	·
person	8.7	-0.011	0.040	·	·	·	·	·
property	38.4	0.052	0.072	·	0.137	0.129	0.133	0.133
sexcrime	2.7	0.460	0.292	·	·	·	·	·
weapons	0.0	0.0	0.0	·	·	·	·	·
hsdeg	1.0	-0.001	0.012	·	·	·	·	·
ged	0.0	0.0	0.0	·	·	·	·	·
colldeg	0.0	0.0	0.0	·	·	·	·	·
voccert	0.0	0.0	0.0	·	·	·	·	·
pednone	0.0	0.0	0.0	·	·	·	·	·
pedged	9.7	-0.011	0.036	·	·	·	·	·
pedhs	0.0	0.0	0.0	·	·	·	·	·
pedcuv	0.0	0.0	0.0	·	·	·	·	·
employed	58.9	-0.117	0.105	-0.200	·	-0.193	·	-0.191
hrsweek	41.1	-0.002	0.002	·	-0.004	·	-0.004	·
wage	0.0	0.0	0.0	·	·	·	·	·
healthben	0.0	0.0	0.0	·	·	·	·	·
jobmanage	0.0	0.0	0.0	·	·	·	·	·
jobbuild	0.0	0.0	0.0	·	·	·	·	·
jobsales	0.0	0.0	0.0	·	·	·	·	·
joboffice	0.0	0.0	0.0	·	·	·	·	·
jobconstr	0.0	0.0	0.0	·	·	·	·	·
jobinstall	0.0	0.0	0.0	·	·	·	·	·
jobprod	0.0	0.0	0.0	·	·	·	·	·
jobtrans	0.0	0.0	0.0	·	·	·	·	·
restitution	53.4	0.064	0.068	0.118	·	·	·	·
childsup	36.9	0.042	0.061	·	·	·	·	·
owncar	20.6	-0.022	0.049	·	·	·	·	·
Number of Variables				6	5	6	6	5
R^2				0.109	0.098	0.108	0.108	0.097
BIC				-20.948	-20.939	-20.749	-20.749	-20.625
Posterior probability				0.036	0.036	0.032	0.032	0.030

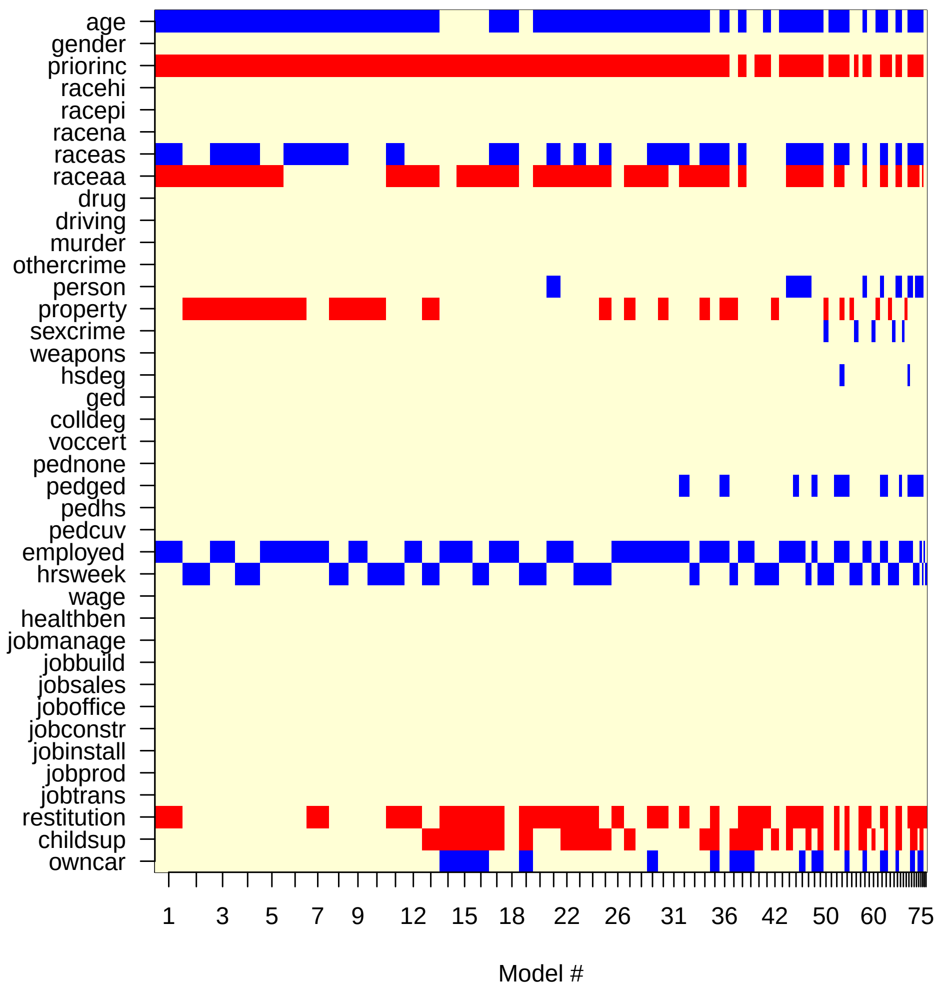

Figure 5: Models Selected by BMA.

number of hours worked is excluded in the top 5 models. In Table 4, the model with the highest posterior probability includes age, the number of prior incarcerations, two race indicator variables, and the two economic variables *employed* and *restitution*. The latter two variables are important from a policy perspective and are substantial in their magnitudes.

A nice feature built into BMA is the ability to produce an image map of the results, presented in Figure 5. This diagram highlights the importance of age, prior incarcerations, and one of the employment variables - either the indicator variable for employment, or the quantitative variable for hours worked per week. When one of these variables is present, BMA drops the other one. The probability is equal to one that either variable is included. This was not detected in EBA. Variables are shown on the vertical axis with either red or blue bars indicating a negative relationship (blue) or a positive relationship (red). Along the horizontal axis, 75 models are indicated with the width of the interval representing of the model's posterior probability (this corresponds to the last line, posterior probability, in Table 4). When a variable is never included (e.g., *gender*), there is no mark in the image.

3.3 Classification and Regression Trees

3.3.1 Overview

The two methods we have discussed so far are parametric in nature and are based on traditional Bayesian linear specifications within the context of a normal-gamma conjugate framework. Our final Bayesian method extends this by finding binary split classification and regression trees (CART) that can overcome potential problems and complex data patterning. Brieman et al. (1984) discuss how CART models can usefully discover the predictive nature of the data. Chipman, George, and McCulloch (1998) develop a fully Bayesian version of CART combining a tree prior and with a tree likelihood. Their procedure seeks high posterior probability binary split trees (T). These trees partition the data into terminal nodes allowing the posterior tree probability to be evaluated. Unlike in traditional CART models, the Bayesian CART model does not necessarily lead to terminal tree nodes that have high degrees of homogeneity. Their method allows for priors to be placed on tree complexity and end node parameters; selection is based on the marginal likelihood of the model using an MCMC algorithm. A comparison of the parametric specifications within the nodes provides useful insights into relationships and some justification for this novel and exploratory approach.

3.3.2 Results

In this paper we use Chipman, George, and McCulloch's (1998) algorithm to classify the return to prison based on the complete set of explanatory variables used in EBA and BMA. We choose a minimally specified prior on the both the tree and the end nodes. Figure 6 illustrates a high posterior probability binary split tree and Table 5 summarizes logit regression coefficients that correspond with the four terminal nodes of this tree for logit parameters associated with criminological and economic variables.[2]

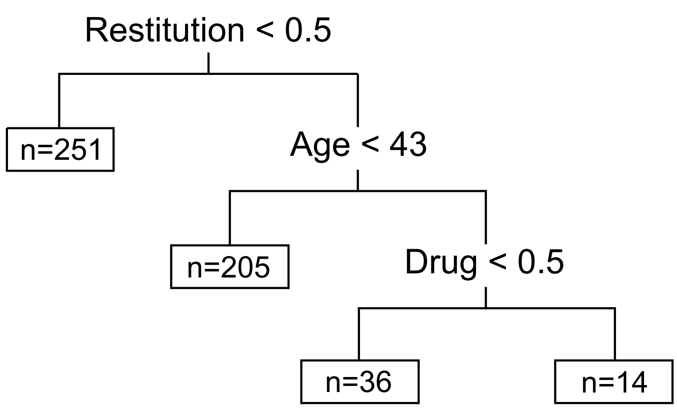

Figure 6: Classification and Regression Tree for Return to Prison.

The model with the reported highest log-likelihood (not necessarily the most visited model) first splits on the binary restitution dummy variable. Of the 506 parolees, 251 do not pay restitution and reach a terminal node. For the 255 parolees

[2]Details on the choice of the prior are discussed in Chipman, George, and McCulloch (1998). The regression coefficients (and splits) are based on standardized data to allow for the comparison of the relative strength of each explanatory variable. All explanatory variables were included in CART and all details are available from the authors for the complete tree.

Table 5: End Node Coefficients and Statistics

	End Node Coefficients				Coefficient Statistics		
	$n = 251$	$n = 205$	$n = 36$	$n = 14$	Mean	Max	Min
age	-0.519	0.649	-0.076	-0.312	-0.065	0.649	-0.519
gender	0.080	0.914	0.215	0.076	0.321	0.914	0.076
priorinc	0.234	0.238	0.762	0.306	0.635	1.234	0.238
employed	-0.610	-0.776	-0.373	-0.031	-0.447	-0.031	-0.776
hrsweek	0.062	-0.734	-0.184	-0.078	-0.234	0.062	-0.734
restitution	-0.050	0.102	0.168	0.700	0.230	0.700	-0.050
childsup	0.484	0.174	0.147	0.556	0.340	0.556	0.147

who do pay restitution, the tree splits on age at 43 years old. The younger group comprised of 205 parolees forms a terminal node and the older group of 50 parolees further splits on the binary variable drug offense to two nodes. In Table 5, the strongest explanatory variables are associated with male and prior incarcerations. These results conform with EBA and BMA results.

4. Comparing the Three Methodologies

Our three Bayesian procedures have utilized a rich data set that measures an array of criminological, demographic, and economic variables. Extreme bounds using a criminological prior detected the importance of the number of prior incarcerations and age as non-fragile predictors of return to prison. Both of these variables are associated with a higher risk of reoffending. The EBA economic prior detected non-fragile posterior bounds for court-mandated payments that include restitution and child support payments. These variables also are associated with a higher risk of recidivism.

Bayesian model averaging also highlighted the importance of prior incarcerations and age as predictors of recidivism, but strongly detected that either being employed or working more hours per week reduces the risk of reoffending. The BMA results gave support to the court-mandated variables as found in EBA, with a probability of inclusion of over 53 percent for restitution and of about 37 percent for child support. The classification and regression tree method reveals that restitution and age are key variables to categorize parolees. In this method the number of prior incarcerations and employment are strong predictors of the return to prison.

In our research, we did not do any screening of variables or model respecification. Our goal was to let the data speak for themselves as loudly as possible in each of the three procedures we used.

5. Conclusions and Policy Recommendations

The astronomical increase in the growth of the prison population in the United States over the last 30 years, coupled with a relatively stable recidivism rate, is a pressing public policy problem. That the growth rate of the shares of state budgets devoted to departments of corrections has surpassed that of public education is a disturbing trend. In the short run, the number of prior incarcerations and the age of a parolee do not appear to provide any clear policy prescriptions, in an of themselves, toward the goal of alleviating the burden on taxpayers. However, one short-run solution that could reduce the total cost of crime is the development of policies aimed at enhancing the opportunities for parolees to gain employment (such as by tax credits for hiring parolees). Furthermore, our data supports the view that policies designed to eliminate or reduce court-mandated payments, such as restitution and/or child support, would lower the likelihood of recidivism, effectively reducing incarceration costs.

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