Recidivism and Social Interactions[*]

(To Appear in the *Journal of the American Statistical Association*)

Sibel Sirakaya[†]
University of Washington, Seattle

Working Paper no. 52
Center for Statistics and the Social Sciences
University of Washington

October 2005

---

[*] Financial support from "The John D. and Catherine T. MacArthur Foundation: Network on Social Interactions and Economic Inequality" and "The Wisconsin Alumni Research Foundation" is gratefully acknowledged. I would like to thank Steven N. Durlauf for his support, advice and encouragement. I would also like to thank Nedim M. Alemdar, William A. Brock, Adrian Raftery and Larry Samuelson, as well as the seminar participants at Bilkent University, Koc University, Penn State University, Purdue University, Sabanci University, Vanderbilt University, University of Miami, University of Washington and University of Wisconsin-Madison for their valuable suggestions and comments. Finally, I would like to thank an anonymous referee for helpful suggestions and the editor of the Journal of the American Statistical Association (Applications and Case Studies), Mark S. Kaiser, for his careful reading of the earlier versions of the manuscript and constructive criticism for improving the manuscript. The usual caveat applies however: all errors are mine.

[†] Sibel Sirakaya is an Assistant Professor of Economics and Statistics, Department of Economics and Statistics, and Center for Statistics and Social Sciences, University of Washington, Campus Box 354320 Seattle, WA 98195-4320. Email: sirakaya@u.washington.edu.

Abstract

Using a national sample, this paper identifies the risk factors for recidivism among Female, Male, Black, White and Hispanic felony probationers. The individual hazard function is assumed to depend on individual and neighborhood characteristics as well as social interactions among probationers. In selecting the covariates from a set of potential candidates, Bayesian model averaging is used both to account for model uncertainty and the subsequent inference. The results point to social interactions as one of the most significant factors affecting recidivism among all gender, ethnicity and race groups. When a frailty parameter is added to account for the possibility of unobserved risk factors shared by probationers within neighborhoods, the empirical results remain robust indicating negligible unobserved neighborhood-level heterogeneity.

Keywords: Recidivism; Social interactions; Model uncertainty; Bayesian model averaging

1 Introduction

According to the Bureau of Justice Statistics Correctional Surveys (as presented in Correctional Populations in the United States, Annual, Prisoners in 2003 and Probation and Parole in the United States, 2003), the prison and jail population in the United States grew from approximately 1.14 million in 1990 to slightly more than 2 million in 2003. There were an estimated 482 prison inmates per 100,000 U.S. residents in 2003, as opposed to 292 at the year end 1990. By the end of 2003, the state prisons were operating between 1 and 16 percent, while the federal prisons were operating 39 percent above capacity. In the face of overcrowded prisons, probation for adults convicted of felony crimes has become a major alternative sentencing in the United States (Benedict and Huff-Corzine, 1997; Petersilia *et al.*, 1985). The number of probationers surpassed 4 million by the end of 2003, up from nearly 2.7 million on December 31, 1990. An estimated 49 percent of all probationers were convicted of a felony.

The swelling probationer population has also stirred a growing debate as to the proper use of probation sentencing in the justice system. Some have argued that recidivism by felony probationers poses a potential threat to the public safety (e.g. Irish, 1989; Petersilia, 1985). Others, however, have concluded that felony probation constitutes not only a viable, but also a cheaper and perhaps more rehabilitative alternative to incarceration (e.g. Benedict and Huff-Corzine, 1997; Clarke *et al.*, 1988; McGaha *et al.*, 1987; Vito, 1986; Whitehead, 1991).

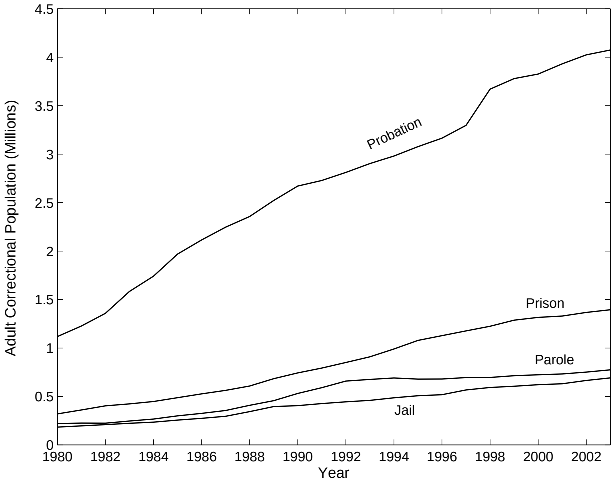

Figure 1.1: Adult Correctional Populations in the United States, 1980-2003.

In view of the situation, it is imperative for policy makers to rethink the mission and the structure of the probation system. In this regard, a proper identification of the risk factors for recidivism among felony probationers becomes crucial for a better risk assessment as well as for designing more effective prevention policies. This paper attempts both to bring a theoretical perspective on recidivism as an outcome of interdependent decision making by probationers, and also to suggest an empirical model to properly identify those factors that increase the risk of recidivism. Towards that, first, an empirical framework is developed for recidivism as a Cox proportional hazard model which also includes social interactions.

Then, model uncertainty is accounted for by employing Bayesian model averaging (BMA) for the selection of covariates and the subsequent inference. Finally, the study uses a national sample to identify the risk factors for recidivism among Female, Male, Black, White and Hispanic felony probationers.

The paper extends the earlier research on recidivism in a number of directions. Conceptually, it departs from its precedents by bringing forth social interactions as a potential risk factor. This is important for policy making as social interactions are accompanied by social multipliers that magnify a singular change in an individual's decision to culminate in a much larger change in the population behavior. Consequently, preventing an individual from recidivating may help reduce the future crime rates by more than what that single individual would have committed. Moreover, social interactions can generate multiple equilibria due again to social multipliers. Even when the group behavior is uniquely determined by fundamentals, a small change in fundamentals may lead to large differences in group behavior. Thus, social multiplier effects may also account for the large spatial differences in recidivism rates reported by the previous studies (ranging from a low of 22 percent in Kentucky (Vito, 1986) to a high of 65 percent in California (Petersilia, 1985)).

The previous literature has typically identified risk factors using stepwise methods, with the single model selected by the procedure used for subsequent statistical analysis. A serious shortcoming of any such procedure is that the reported uncertainty for the values such as future predictions or parameter estimates reflects only *within* model uncertainty, ignoring *between* model uncertainty-the uncertainty associated with the model selection procedure itself. The paper employs BMA to account for model uncertainty as well, and shows that BMA leads to a better evaluation of the risk factors for recidivism, as well as improved risk assessment for the potential recidivists.

An additional contribution of the study is the scope of the data set, which is a large national sample that includes felony probation cases from each of the major regions in the United States. Thus, we are able to delineate more clearly the differences in recidivism experiences of racial and ethnic groups across jurisdictions.

From the empirical analysis, social interactions emerge as one of the most significant contributor to recidivism among all gender, ethnicity and race groups. Among other significant factors are: being male, being young, lack of employment, having a drug abuse history and prior felony convictions, and living in neighborhoods with high serious violent crime per capita for Blacks; being male, being young, lack of employment, having a drug abuse history and prior felony convictions, being convicted of a property offense, robbery or drug trafficking, and living in Republican neighborhoods for Whites; being young, lack of employment, having a drug abuse history and being convicted of a property offense, robbery or drug trafficking for Hispanics; lack of employment, having prior felony convictions and being under stringent supervision during probation for Females; being young, lack of employment and education, having a drug abuse history and prior felony convictions, and living in neighborhoods with low percentages of persons below poverty level for Males. The empirical results remain robust when a frailty parameter is added to account for the possibility of unobserved risk factors shared by probationers within neighborhoods.

The balance of the paper is as follows. Section 2 provides a brief review of the literature on recidivism and interactions-based crime models. Section 3 develops an interactions-based model of recidivism within the tradition of Cox proportional hazard models. In Section 4, BMA is introduced and its extension to variable selection in the recidivism model is discussed. Section 5 introduces the data set. Section 6 reports and interprets the results of the BMA analysis. The robustness of the findings is tested and a comparison is done with stepwise methods. Conclusions follow.

2 Literature

Existing studies report significant spatial differences in recidivism rates among felony probationers, from a low of 22 percent in Kentucky (Vito, 1986) to a high of 65 percent in California (Petersilia, 1985). Despite these large spatial differences, prior research has focused solely on individual characteristics and criminal history of probationers in a single state or in a number of counties, ignoring the potential influence of various types of *interactions* among probationers on the differential recidivism experiences across locales. Age, race, education, income, marital status, prior criminal history, and type of crime committed are among the risk factors reported as significant (Petersilia, 1985; Vito, 1986; McGaha *et al.*, 1987; Clarke *et al.*, 1988; Irish, 1989; Benedict and Huff-Corzine, 1997).

More recently, the crime literature in economics has turned to models that explicitly incorporate interactions among criminals to explain the differential crime rates across locales. However, to the best of my knowledge, there is no study on recidivism of felons on probation per se. Before conceptualizing recidivism within the context of social interactions, a brief review of some of the key results on crime and social interactions in economics literature is in order.

In Sah (1991), police cannot arrest more than a fixed number of criminals. Thus, the larger the number of criminals, the lower the probability of arrest, which in turn reduces the cost of engaging in a criminal activity. Freeman *et al.* (1996) argue that high crime rates today may cause some youths to postpone investments in human capital-they may drop out of high school lured by the prospects of higher returns on criminal activities today. This will in turn cause inertia in criminal behavior since undereducated youth will have limited access to legal opportunities and hence will be more prone to commit crimes in the future. On the empirical side, in order to explain the large cross-sectional variation of crime rates, Glaeser *et al.* (1996) model interactions among individuals within cities. They suggest that interdependencies between agents' decisions about crime (social interactions) are necessary to explain the high variability of crime rates across space. They argue that if agents' decisions were independent, then city crime levels would have represented the averages of large numbers of independent decisions, and thus should have been closer to the expected population means. In the absence of interdependent decisions, the large differences in crime rates across space must then be explained by sufficiently different economic conditions (or levels of deterrence) in the different areas. They claim, however, that less than 30 percent of the variation in cross-city rates can be explained by differences in local area characteristics based on OLS regressions that control for local area attributes. The remaining variance is too high to be compatible with a model where agents' decisions about crime are independent.

Glaeser *et al.* (1996) identify statistical independence with the absence of interdependent decisions. However, even in the absence of social interactions, agents within a city may behave similarly because they have similar individual characteristics and/or face the same institutional environments, or the crime rates may vary with the exogenous characteristics of the group of agents within a city. This implies that even in the absence of social interactions, city crime levels may not represent the averages of large numbers of independent decisions. The empirical model in the present study improves upon Gleaser *et al.* (1996) by disentangling the covariations in times to recidivism that are due to agents' interdependent choices, social interactions, from the covariations that originate from the exogenous and/or correlated social effects mentioned above.

3 Model

3.1 Basic Ideas

Manski (1995, p.128) classifies social effects into three types. The first is *endogenous* social effects, which arise when choices made by an individual are affected, not through market transactions, by actions of the others. Social learning, conformity and sanctions are some of the mechanisms giving rise to endogenous social effects. Endogenous social effects imply that the net benefit of recidivating increases as others also recidivate (e.g., while one person is being arrested, it might be harder to arrest someone else for the police). Throughout the study, I use the term social interactions for endogenous social effects in keeping with Brock and Durlauf (2001a, 2001b). The second type of social effects is *contextual* (or exogenous) effects, which occur when an individual's behavior is affected by the exogenous characteristics of the group of which he is a member. For instance, contextual effects appear if recidivism rates vary with the socioeconomic composition of groups. Finally, *correlated* effects occur when individuals of the same group behave similarly because they have similar individual characteristics or face the same institutional environments, such as state sentencing and incarceration practices.

To see the difference between various social effects, consider a recidivism prevention program that successfully decreases the recidivism rate for a group of probationers who are drug abusers and known to engage in criminal activity to 'feed' their drug habit. Whether there exists social interactions depends on the prevention mechanism involved. If the program decreases the likelihood of recidivating, say, through providing a free drug treatment, then there is a correlated effect according to Manski's definition. However, if the probationer's use of drug treatment depends on the commonness of the probationers who also receive treatment in the group, then a social interaction exists. This may be due to, for example, social learning. Probationers who receive the treatment may communicate with others as to the benefits of drug treatment, decreasing the uncertainty faced by succeeding probationers, thereby increasing its use.

From a policy-making perspective, the distinction between exogenous social effects and social interactions is important because social interactions generate social multipliers, causing a singular change in one individual's decision to culminate in a multiple change in the population behavior. Preventing one person from recidivating may then help reduce the future recidivism rates by more than what that single individual would have committed. Consider the recidivism prevention program example. In the presence of social interactions, a probationer's decision not to recidivate, will, through for example social learning, decrease the likelihood of recidivating by the others. Thus, a policy that targets, and operates through social interactions will have a very different effect on recidivism than a policy that changes only the exogenous determinants.

3.2 Recidivism and Social Interactions

This section develops an empirical model that allows us to statistically disentangle the contribution of social interactions to recidivism from the contributions of exogenous and correlated social effects. Social interactions are modelled as affecting the probability of transition from one state (remaining crime free) to another (recidivating). Using the standard notation (e.g. Amemiya, 1985), let T denote the duration from $t = 0$ that a probationer remains crime free. The probability that this duration is less than t, $Pr(T < t)$, is denoted as $F(t)$. For any interval δt, the probability that a crime free probationer at t recidivates by $t + \delta t$ is

$$Pr(t \leq T < t + \delta t | T \geq t) = \frac{Pr(t \leq T < t + \delta t, T \geq t)}{Pr(T \geq t)} \tag{3.1}$$

From Eq. (3.1), two standard functions of interest can be defined. First, the hazard function $\lambda(t)$ is defined as

$$\lambda(t) = \lim_{\delta t \to 0} \frac{Pr(t \leq T < t + \delta t | T \geq t)}{\delta t} = \frac{F'(t)}{1 - F(t)} \tag{3.2}$$

Second, the survivor function $S(t)$ is defined as $1 - F(t)$

$$S(t) = \exp[-\int_0^t \lambda(z) dz] \tag{3.3}$$

Cox (1972) proportional hazard model specifies the hazard rate for individual i with covariate vector $\mathbf{z}_i$ to be

$$\lambda(t, \mathbf{z}_i) = \lambda_0(t) \exp(\theta' \mathbf{z}_i) \tag{3.4}$$

where $\lambda_0(t)$ is the baseline hazard function at time t, left unspecified in Cox's formulation, and θ is a vector of unknown parameters.

In the context of recidivism, the hazard function for probationer i is assumed to depend on i's individual characteristics, $\mathbf{x}_i$, characteristics of i's neighborhood, $\mathbf{y}_{n(i)}$, and i's subjective expectation of a neighborhood behavioral measure, $\mathbf{m}^e_{n(i)} = (\nu^e_{n(i)}, \omega^e_{n(i)})'$, where $\nu^e_{n(i)}$ and $\omega^e_{n(i)}$ are i's subjective expectations of the proportion of probationers who recidivate by some duration τ in i's neighborhood and the mean time to recidivate among them, respectively. Since, a probationer is required to live in the jurisdiction that passed the probation sentence, the neighborhood of probationer i, $n(i)$, is assumed to be the jurisdiction. That is, in the current context, probationers do *not* endogenously coalesce into neighborhoods. Hence, Eq. (3.4) takes the following form

$$\lambda(t, \mathbf{x}_i, \mathbf{y}_{n(i)}, \mathbf{m}^e_{n(i)}) = \lambda_0(t) \exp(\alpha' \mathbf{x}_i + \beta' \mathbf{y}_{n(i)} + J' \mathbf{m}^e_{n(i)}) \tag{3.5}$$

The probability that probationer i recidivates by duration t is given by

$$F(t \mid \mathbf{x}_i, \mathbf{y}_{n(i)}, \mathbf{m}^e_{n(i)}) = 1 - \exp[-\Lambda_0(t)\exp(\alpha'\mathbf{x}_i + \beta'\mathbf{y}_{n(i)} + J'\mathbf{m}^e_{n(i)})] \tag{3.6}$$

where $\Lambda_0(t) = \int_0^t \lambda_0(z)dz$ is an integrated baseline hazard. The associated density for the time to recidivate is

$$\begin{aligned} f(t \mid \mathbf{x}_i, \mathbf{y}_{n(i)}, \mathbf{m}^e_{n(i)}) = {} & \lambda_0(t)\exp(\alpha'\mathbf{x}_i + \beta'\mathbf{y}_{n(i)} + J'\mathbf{m}^e_{n(i)}) \\ & \times \exp[-\Lambda_0(t)\exp(\alpha'\mathbf{x}_i + \beta'\mathbf{y}_{n(i)} + J'\mathbf{m}^e_{n(i)})] \end{aligned} \tag{3.7}$$

and the expected time to recidivate for probationer i, conditional on these controls, is

$$E(t \mid \mathbf{x}_i, \mathbf{y}_{n(i)}, \mathbf{m}^e_{n(i)}) = \int_0^\infty t f(t \mid \mathbf{x}_i, \mathbf{y}_{n(i)}, \mathbf{m}^e_{n(i)})dt \tag{3.8}$$

To close the model, it is necessary to specify how expectations are formed. I assume that probationers all possess rational expectations. Thus

$$\mathbf{m}^e_{n(i)} = \mathbf{m}_{n(i)} = \begin{pmatrix} \displaystyle\int dF_x \sum_{i \in n(i)} F(\tau \mid \mathbf{x}_i, \mathbf{y}_{n(i)}, \mathbf{m}_{n(i)}) \\ \displaystyle\int \mathbb{I}_{\{i \in \psi_{n(i)}\}} E[t \mid \mathbf{x}_i, \mathbf{y}_{n(i)}, \mathbf{m}_{n(i)}] dF_{\mathbf{x}} \end{pmatrix} \tag{3.9}$$

where $F_{\mathbf{x}}$ is the probability distribution of individual characteristics within neighborhood $n(i)$, $\psi_{n(i)}$ is the set of probationers who recidivate by duration τ in neighborhood $n(i)$, and

$$\mathbb{I}_{\{i \in \psi_{n(i)}\}} = \begin{cases} 1 & \text{if } i \in \psi_{n(i)}, \\ 0 & \text{otherwise.} \end{cases} \tag{3.10}$$

Letting $\mathbf{z}_i = (\mathbf{x}'_i, \mathbf{y}'_{n(i)}, \mathbf{m}'^e_{n(i)})'$ and $\theta = (\alpha', \beta', J')'$, the associated likelihood function for the data is given by

$$L = \prod_{i=1}^{n} \lambda_0(t_i)\exp(\theta'\mathbf{z}_i)\exp[-\Lambda_0(t_i)\exp(\theta'\mathbf{z}_i)] \prod_{i=n+1}^{I} \exp[-\Lambda_0(t_i)\exp(\theta'\mathbf{z}_i)] \tag{3.11}$$

where $t_i, i = 1, 2, \ldots, n$ are the completed spells (probationer i recidivated at time t_i), and spells $t_i, i = n+1, \ldots, I$ are right censored at time t_i (i.e., these are the spells that were ongoing at the end of the observation period). Eq. (3.11) assumes that there are no ties between times of failure; for simplicity, I do not consider modifications needed when there are ties.

Combining the exponential functions that appear in both terms, and rewriting the combined term

$$L = \prod_{i=1}^{n} \lambda_0(t_i)\exp(\theta'\mathbf{z}_i)\exp\left\{ -\int_0^\infty \left[\sum_{h \in R(t)} \exp(\theta'\mathbf{z}_i) \right] \lambda_0(t)dt \right\} \tag{3.12}$$

where $R(t) = \{i|t_i \geq t\}$. Cox's partial maximum likelihood $\hat{\theta}$ maximizes

$$L_1 = \prod_{i=1}^{n} \frac{\exp(\theta' \mathbf{z}_i)}{\sum\limits_{h \in R(t_i)} \exp(\theta' \mathbf{z}_i)} \tag{3.13}$$

L_1 is a part of L because as L can be written as $L = L_1 L_2$, where

$$L_2 = \prod_{i=1}^{n} \left[\sum_{h \in R(t_i)} \exp(\theta' \mathbf{z}_i) \lambda_0(t_i) \right] \exp \left\{ - \int_0^{\infty} \left[\sum_{h \in R(t)} \exp(\theta' \mathbf{z}_i) \right] \lambda_0(t) dt \right\} \tag{3.14}$$

Because L_1 does not depend on $\lambda_0(t)$, θ can be estimated without specifying $\lambda_0(t)$. Identification in population requires that the expected value of the Hessian matrix of $logL_1$ is nonsingular at the self-consistent solution (3.9). Identification is a concern in interactions-based models as the group versus individual determinants of individual behavior are likely to be correlated (See Brock and Durlauf (2001a) for an extensive discussion of identification in social interactions-based models). However, it is not an issue here as, by (3.9), group and individual determinants are nonlinearly related.

4 Accounting for Model Uncertainty with Bayesian Model Averaging

To proceed further, a specific collection of covariates should be selected. The standard approach to model selection is to search over many classes of models, usually through stepwise methods (Efroymson, 1960), and then pick the one that "best" fits the data. Once the model is "found", then it is used for the subsequent statistical analysis, the results are reported and interpreted. The reported uncertainty for the values such as the future predictions or the parameter estimates, however, reflects only *within* model uncertainty. Ignoring *between* model uncertainty–uncertainty associated with the model selection procedure itself–results in the underestimation of overall uncertainty, overestimation of a particular model being "correct" and poorer predictive ability (Chatfield, 1995; Draper, 1995; Madigan and Raftery, 1994; Volinsky, 1997; Volinsky, *et al.* 1997).

One possible approach to model uncertainty is to obtain several potential "best" models, each of which is strongly supported by the data. Though this approach addresses model uncertainty, it does not offer a way to combine the results of different models and to interpret the results when the models indicate qualitatively different conclusions.

Bayesian solution to this problem is to select a number of most likely models from a set of potential candidates and then to combine the results from the former by averaging with weights based on the posterior probabilities, a method known as Bayesian model averaging. BMA approach accounts for model uncertainty in both predictions and parameter estimates. The resulting estimates of uncertainty incorporate between model uncertainty and thus may better reflect the true uncertainty in the estimates. The following section provides a brief overview of how BMA can be extended to Cox proportional hazards model as suggested by Volinsky *et al.* (1997).

4.1 Bayesian Model Averaging and Cox Proportional Hazard

Let Δ be any unknown quantity of interest and $\mathcal{M}=\{M_1, \ldots, M_K\}$ be the set of all models under consideration. The posterior distribution of Δ given the data D is

$$Pr(\Delta|D) = \sum_{k=1}^{K} Pr(\Delta|M_k, D) Pr(M_k|D) \tag{4.1}$$

which is an average of the posterior distributions under each model weighted by the corresponding posterior model probabilities. The posterior probability for model M_k is given by

$$Pr(M_k|D) = \frac{Pr(D|M_k)Pr(M_k)}{\sum_{l=1}^{K} Pr(D|M_l)Pr(M_l)} \tag{4.2}$$

where

$$Pr(D|M_k) = \int Pr(D|\theta_k, M_k) Pr(\theta_k|M_k) d\theta_k \tag{4.3}$$

is the integrated likelihood of model M_k, θ_k is the vector of parameters of model M_k, $Pr(\theta_k|M_k)$ is the prior density of θ_k under model M_k, $Pr(D|\theta_k, M_k)$ is the likelihood, and $Pr(M_k)$ is the prior probability that M_k is the true model. All probabilities are implicitly conditional on $\mathcal{M}$, the set of all models under consideration.

The predictive distribution of Δ given a particular model M_k, $Pr(\Delta|M_k, D)$, is found by integrating out the model parameter θ_k:

$$Pr(\Delta|M_k, D) = \int Pr(\Delta|\theta_k, M_k, D) Pr(\theta_k|M_k, D) d\theta_k \tag{4.4}$$

When there are many potential covariates, the finite sum (4.1) can quickly become unmanageable. Madigan and Raftery (1994) suggest averaging only over the "best" models as an approximation to averaging over all models, where "best" is determined by the posterior model probability. Thus, only models belonging to the set below are included in the sum (4.1).

$$\mathcal{A} = \left\{ M_k : \frac{\max_l\{Pr(M_l|D)\}}{Pr(M_k|D)} \leq C \right\} \tag{4.5}$$

It is shown in Madigan and Raftery (1994) and Raftery *et al.* (1997) that $C = 20$ provides a good approximation to averaging over the entire model space. In the following BMA analysis of recidivism, $C = 20$ is used, and averaging is done only over models with posterior model probabilities at least 1/20 of that of the best model.

Eq. (4.1) has three components that are hard to compute. The first is the predictive distribution, $Pr(\Delta|M_k, D)$. The integral (4.4) does not have a closed form solution for the Cox-proportional hazard models. Volinsky *et al.* (1997) use the MLE approximation:

$$Pr(\Delta|M_k, D) \approx Pr(\Delta|M_k, \hat{\theta}_k, D) \tag{4.6}$$

The second integral (4.3), the integrated likelihood $Pr(D|M_k)$, is in general also intractable in survival regression models. In regular statistical models (those in which MLE is consistent and asymptotically normal), Raftery (1996) suggests that Laplace transforms be used for approximation. Consequently, we have

$$Pr(D|M_k) = logPr(D|\hat{\theta}_k, M_k) - (d_k/2)logn + O(1) \tag{4.7}$$

where d_k is the dimension of θ_k and n is the total number of cases. Note that the resulting expression is the approximation to Bayesian information criterion (BIC) derived in Schwarz (1978).

To proceed further with Eq.(4.2), model priors need to be specified. As a plausible and perhaps also a "neutral" choice, all recidivism models under consideration are assumed to be a priori equally likely. With quite large data spaces (involving up to 10^{12} models) and about 20 data sets, previous research reports no perverse effects from putting uniform priors over the models (Raftery *et al.*, 1993; Madigan and Raftery, 1994; Madigan *et al.*, 1996).

Finally, the best model (defined as that which has the largest BIC, corresponding to the model with the highest posterior model probability) must be identified so that averaging can be done over only those models with posterior probabilities no less than $1/C$ of the best model. To efficiently identify the models in $\mathcal{A}$, Volinsky, *et al.* (1997) propose the "leaps and bounds" algorithm of Furnival and Wilson (1974) which was originally developed for model selection in linear regression.

Linear regression by leaps and bounds provides the top q models of each model size, where q is chosen by the user. The MLE $\hat{\theta}_k$, var($\hat{\theta}_k$), and R^2 for each model M_k are also returned. Using the fact that for two models A and B, where A and B are each subsets of the full parameter set, if $A \subset B$ then RSS (A)> RSS (B), the method eliminates large portions of model space by sweep operations on the matrix:

$$\begin{pmatrix} \text{X'X} & \text{X'y} \\ \text{y'X} & \text{y'y} \end{pmatrix} \tag{4.8}$$

which plays a key role in Lawless and Singhal (1978), who modifies the leaps and bounds algorithm for nonlinear regression models. The method provides an approximate likelihood ratio test statistics, and therefore, an approximate BIC value. Kuk (1984) uses the algorithm in Cox regression models in order to find the single best model. Volinsky *et al.* (1997), however, utilizes it to help locate the models in $\mathcal{A}$ that are to be averaged over.

The Lawless and Singhal method proceeds as follows: Let θ be the parameter vector of the full model and let θ_k be the vector for a given submodel k. Rewrite θ_k as (θ_1, θ_2) so that Model M_k corresponds to the submodel $\theta_2 = 0$. Also, let

$$V = \mathcal{I}^{-1} = \begin{pmatrix} V_{11} & V_{12} \\ V'_{12} & V_{22} \end{pmatrix} \tag{4.9}$$

denote the inverse observed information matrix. If $L(\hat{\theta})$ is the maximized likelihood under the full (unrestricted) model, and $L(\tilde{\theta})$ is the maximized likelihood under $\theta_2 = 0$, then

$$\Omega = -2[logL(\tilde{\theta}) - logL(\hat{\theta})] \tag{4.10}$$

is the usual likelihood ratio statistic for the test of the submodel *versus* the full model while

$$\Omega' = \hat{\theta}_2 V_{22}^{-1} \hat{\theta}_2$$

is an approximation to Ω based on the Wald statistic. Finally, replace the matrix in (4.8) with

$$\begin{pmatrix} \mathcal{I} & \mathcal{I}\hat{\theta} \\ \hat{\theta}'\mathcal{I} & \hat{\theta}'\mathcal{I}\hat{\theta} \end{pmatrix}$$

and perform the same matrix sweep operations from the leaps and bounds algorithm on it. Thus, this revised algorithm provides

1. an estimate of the best q proportional hazards models for each model size,
2. the LRT approximation Ω' for each model,
3. an approximation to $\tilde{\theta}$, the MLE for the parameters of the submodel, and
4. the asymptotic covariance matrix V_{11}^{-1}

As long as q is large enough, this procedure returns the models in $\mathcal{A}$ plus many models not in $\mathcal{A}$. Volinsky *et al.* (1997) use the approximate LRT to reduce the remaining subset of models to those most likely to be in $\mathcal{A}$. This reduction step keeps only the models whose posterior probabilities are at least $1/C'$ of the posterior model probability of the best model, where C' is greater than C. For the recidivism model, it is assumed that $C' = C^2$, which turns out to be large enough to guarantee that no model in $\mathcal{A}$ will be lost.

The returned models are then estimated by standard survival regression technics, the exact BIC value (corresponding to a posterior probability by Eq. (4.7)) for each is computed, and those that are not in $\mathcal{A}$ are eliminated. The posterior model probabilities are then normalized over the selected set. The posterior mean of the regression coefficients and standard errors are as follows:

$$\begin{aligned}\hat{\theta}_{BMA} = E_M(\hat{\theta}) &= \sum_{k=1}^{K} \hat{\theta}_k Pr(M_k|D) \\ &= \frac{\sum_{k=1}^{K} Pr(M_k|D)\hat{\theta}_k}{\sum_{k:\theta_k \in M_k}^{K} Pr(M_k|D)} \times \sum_{k:\theta_k \in M_k}^{K} Pr(M_k|D) \\ &= E[\hat{\theta} \mid \theta_k \in M_k] \times Pr(\theta \neq 0)\end{aligned}$$

which is the *conditional posterior mean* of θ multiplied by its posterior probability. For the variance of the regression coefficient, let $p_k = Pr(M_k|D)$ and $V_k = \text{Var}(\hat{\theta}|M_k, D)$. Then:

$$\begin{aligned}Var(\hat{\theta}) &= E[\hat{\theta}^2] - (\sum_{k=1}^{K} p_k \hat{\theta}_k)^2 \\ &= \sum_{k=1}^{K} p_k (V_k + \hat{\theta}_k^2) - (\sum_{k=1}^{K} p_k \hat{\theta}_k)^2 \\ &= \sum_{k=1}^{K} p_k V_k + \sum_{k=1}^{K} p_k \hat{\theta}_k^2 - (\sum_{k=1}^{K} p_k \hat{\theta}_k)^2\end{aligned}$$

$$= \sum_{k=1}^{K} p_k V_k + \sum_{k=1}^{K} p_k (\hat{\theta}_k - \sum_{k=1}^{K} p_k \hat{\theta}_k)^2$$

The first term is the weighted variance across the models. The second component reflects the stability of estimates. The higher the difference in estimates across models, the higher will be the posterior variance. Hence, the standard errors directly take model uncertainty into account.

The posterior probability that a regression coefficient is nonzero is calculated by adding the posterior probabilities from all the models that contain the specific variable. The interpretation of a posterior probability is as follows: less than 50%: evidence against the effect; 50-75%: weak evidence for the effect; 75-95%: positive evidence; 95-99%: strong evidence; and greater than 99%: very strong evidence (Kass and Raftery, 1995).

4.2 Predictive Performance

To assess the predictive performance of BMA relative to competing methods, Volinsky *et al.* (1997) suggest the following procedure. First, randomly split the data set into two halves and then apply model selection methods to the one half, called the build data (D^B). Next, define a predictive density for each method in the remaining half, the test data, or D^T, from the corresponding coefficient estimates. Then, a log score for any given model M_k is based on the observed ordinate of the predictive density for the methods in D^T:

$$\sum_{d \in D^T} log Pr(d|M_k, D^B) \tag{4.11}$$

Similarly, the predictive log score for BMA is

$$\sum_{d \in D^T} log \left\{ \sum_{M \in \mathcal{M}} Pr(d|M, D^B) Pr(M|D^B) \right\} \tag{4.12}$$

where $\mathcal{M}$ is the set of models selected by BMA. The Cox model does not directly provide a predictive density, but rather an estimated predictive CDF which is a step function (Breslow, 1975). Therefore, differentiation is not possible to obtain a density. In the spirit of Cox's partial likelihood (3.14), Volinsky *et al.* (1997) design an alternative to the predictive density:

$$Pr(d|M_k, D^B) = \left\{ \frac{\exp(\mathbf{z}_i^T \hat{\theta}_k)}{\sum_{h \in R(t_i)} \exp(\mathbf{z}_h^T \hat{\theta}_k)} \right\}^{w_i} \tag{4.13}$$

where w_i is an indicator for whether or not subject i is censored. By substituting Eq. (4.13) into Eq.s (4.11) and (4.12) above, an analogue to a log score (Good, 1952) called the partial predictive score (PPS) is obtained. The PPS is larger for the method which assigns higher probability to the events that occur in the test set.

5 Data

The data on individual characteristics, criminal histories and arrest activities of probationers are obtained from the nation's largest survey of felons on probation (U.S. Dept. of Justice, Bureau of Justice Statistics. Recidivism of Felons on Probation, 1986-1989: [United States] [Computer file]. Conducted by Mark A. Cunniff and the National Association of Criminal Justice Planners. 2nd ICPSR ed. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [producer and distributor], 1994.). The arrest activity of a sample of 12,369 felons from 32 jurisdictions that represents the total of 306,000 felons from 100 jurisdictions who were sentenced to probation in 1986 was observed until about June 1990. I also use data on jurisdiction characteristics, which are obtained from the City and County Data Books of U.S. Census Bureau. The City and County Data Books provide jurisdiction level data for the years 1985 and 1990.

5.1 A Brief Overview of the Data

The probationers who were out of study due probation violations or misdemeanor conviction cases (3.8 percent of the sample), whose probation began before 1986 sentence (7.7 percent of the sample) and for whom there is no information on arrest activity (8.2 percent of the sample) are excluded from the analysis. Table 5.1 reports the percentage of probationers who were rearrested over the data collection period for each gender, ethnicity and race group in the remaining sample. The variables used in the study are described in Table 5.2. The property taxes data for Baltimore City and St. Louis City used in the analysis are for the fiscal year 1990-1991. The serious violent crimes included are rape, robbery, aggravated assault, and homicide. 'Supervision level' and 'Employment history' variables are recoded so that they have a natural ordering. Numbers reported in Tables 5.1 and 5.2 exclude missing values.

Almost all cases in the sample have missing values for at least one of the variables. The missingness of the variables included in the study ranges from a 0.5 percent (probation term) to a 32.6 percent (supervision level). Missing data is handled with the multiple imputation method. Missing values are imputed with the expectation maximization with importance sampling (EMis) algorithm (King *et al.* 2001) to obtain five complete data sets. EMis can be implemented using the public domain AMELIA software (Honaker *et al.* 2001).

Gender, Race and Ethnicity	*% Rearrested after probation sentencing*
Males	46.1
Females	30.2
Whites	37.8
Blacks	55.3
Amer. Indians/Alaskan Natives	41.1
Asians/Pacific Islanders	27.3
Hispanics	46.2
Total Sample	43.9

Table 5.1: Rearrest Rates by Gender, Race and Ethnicity

Jurisdictions included in the sample are reported in Table 5.3. Franklin County, OH is excluded from the analysis due to its small representation in the sample.

Variable	*Range*	*Mean*
Individual Characteristics		
Sex	1≡ Male, 2≡ Female	1.14
Age	1≡ Under 20 2≡ 20-24 years old 3≡ 25-29 years old 4≡ 30-39 years old 5≡ 40-49 years old 6≡ 50 and older	2.97
Race	1≡ White, 2≡ Black 3≡ Amer. Indian/Alaskan Native 4≡ Asian/Pacific Islander 5≡ Other	1.49
Ethnicity	1≡ Hispanic, 2≡ Non-Hispanic	1.78
Marital status	1≡ Married/Widower 2≡ Divorced/Separated 3≡ Single	2.33
Education level	1≡ Grade school 2≡ Some high school 3≡ High school (GED) 4≡ Some college 5≡ College degree	2.54
Prior felony convictions	1≡ None, 2≡ One 3≡ Two or more	1.36
Drug abuse history	1≡ No abuse 2≡ Occasional abuse 3≡ Frequent abuse	1.77
Supervision level	1≡ Administrative, 2≡ Minimum 3≡ Medium, 4≡ Maximum 5≡ Intense	2.82
Type of crime committed	1≡ Murder/nonneg manslaughter 2≡ Rape, 3≡ Robbery 4≡ Aggravated assault, 5≡ Burglary 6≡ Larceny/auto theft 7≡ Drug trafficking, 8≡ Other felony	5.60
Employment history	1≡ Under 40% 2≡ 40-60% 3≡ 60% or more	1.96
Probation term (months)	1-144	45.46
Status	0≡censored, 1≡rearrest	0.44
Jurisdiction Characteristics		
Population, 1984	429,623-8,007,891	1,769,749.56
Non-white (%), 1984	6.16-65.54	21.34
Hispanic (%), 1990	0.70-49.70	14.74
Female-headed households with children under age 18 (%), 1990	33.40-64.20	54.34
Persons over age 25 with 4 or more years of college(%), 1990	14.90-42.20	24.31
Persons over age 25 with 12 or more years of schooling(%), 1990	60.70-88.20	76.43
Persons below poverty level (%), 1989	3.70-24.60	13.13
Owner-occupied housing (%), 1990	17.87-80.45	56.43
Property taxes (%), 1986-1987	13.70-97.90	65.98
Republican votes cast for the president (%), 1992	15.90-48.80	32.93
Serious violent crime per capita, average of 1985 and 1991	0.002-0.103	0.014
Unemployment rate,1986	3.90-10.30	6.31
Time from probation to first felony rearrest (days)	1-1524	468.97

Table 5.2: Descriptions of the Variables Used in the Study

1. Baltimore City, MD
2. Baltimore County, MD
3. Bexar County, TX
4. Cook County, IL
5. Dade County, FL
6. Dallas County, TX
7. Denver, CO
8. Erie County, NY
9. Franklin County, OH
10. Harris County, TX
11. Hennepin County, MN
12. Honolulu County, HI
13. Jefferson County, KY
14. King County, WA
15. Kings County, NY
16. Los Angeles County, CA
17. Maricopa County, AZ
18. Milwaukee County, WI
19. Monroe County, NY
20. Nassau County, NY
21. New York County, NY
22. Oklahoma County, OK
23. Orange County, CA
24. Philadelphia, PA
25. San Bernardino County, CA
26. San Diego County, CA
27. San Francisco, CA
28. Santa Clara County, CA
29. St. Louis City, MO
30. St. Louis County, MO
31. Suffolk County, NY
32. Ventura County, CA

Table 5.3: Jurisdictions Included in the Sample

5.2 Variables

Dependent Variable

Consistent with previous studies (e.g. Benedict and Huff-Corzine, 1997; Clark *et al.*, 1988; Irish, 1989; McGaha *et al.*, 1987; Petersilia, 1985; Vito, 1987; Whitehead, 1991), the dependent variable is the first *felony* rearrest after probation sentencing. Specifically, I employ the length of time from felony probation sentencing to a probationer's first felony rearrest. Reviewing over 90 studies using the term recidivism, Maltz (1984) derives nine categories used to indicate that recidivism has occurred: arrest, reconviction, incarceration, parole violation, parole suspension, parole revocation, offense, absconding, and probation. He concludes that "recidivism definition of choice appears to be ... arrest recidivism." An additional advantage of defining recidivism as rearrest is that the arrest data supplied by law enforcement agencies are more complete and reliable than prosecutorial, court and correctional data. Thus, the most practical measure of recidivism is rearrest (Benedict and Huff-Corzine, 1997; Shinnar and Shinnar, 1975; Visher *et al.*, 1991).

Potential Explanatory Variables

Social Interactions: Section 3.2 assumes that probationers reference on the entire group of probationers in their neighborhoods through their subjective expectations of the within-neighborhood percentage of recidivists and the mean time to recidivate among them. Under the self-consistency assumption, the percentage of recidivists in jurisdictions over the data collection period and the average time to rearrest among them are employed to approximate their population counterparts.

Gender: A small proportion of the sample, 13.6 percent, consists of females. Research on the recidivism by the female offenders has been lacking as compared with the males. However, gender might play an important role in the recidivist behavior of probationers.

Age: Prior research finds age as a significant factor affecting recidivism (e.g. Clarke *et al.*, 1988; Irish, 1989). It is generally reported that younger probationers are more likely than older probationers to recidivate.

Race: The most common justification for the inclusion of race in the study of recidivism is the over-representation of Blacks arrested, convicted and consequently sentenced in the criminal justice system. For example, 59.6 percent of our sample consists of Whites, 36 percent consists of Blacks. While there are more Whites in the sample, the rearrest rate while on probation is notably higher for Blacks; 55.3 percent compared to 37.8 percent for Whites.

Ethnicity: Offenders are classified as Hispanic or Non-Hispanic in the sample. A small portion of the sample, 22 percent, consists of Hispanics. However, the rearrest rate for Hispanics is notably higher (46.2 percent) than that of Whites (37.8 percent). Prior research on the treatment of Hispanics in the criminal justice system is inconclusive. Some studies conclude that Hispanics are treated differently (e.g. LaFree, 1985; Mandel ,1979). Others, however, indicate that there is little or no difference in their treatment (e.g. Unnever, 1981).

Marital Status: Prior research that include marital status (household composition) in their models finds it as a significant factor affecting recidivism (Landis *et al.*, 1969; Petersilia, 1985, Petersilia and Turner, 1990). In the sample, married probationers had a slightly lower level of supervision than single probationers. Offenders with a spouse and/or children are believed to be less likely to recidivate because of the responsibilities associated with having a family and the stability the familial institution provides.

Education: Education is measured as the educational level attained at the time of the probation intake in the sample. Probationers who had an education level of high school and below consist of 85.4 percent of the sample. According to a Bureau of Justice statistics report "among U.S adults who neither graduated from a high school nor earned a general equivalence degree (GED), almost 6 percent of Blacks and 1 percent of Whites were in a Federal or State prison serving a sentence of one year or more" (Bureau of Justice Statistics, 1995).

Prior Felony Convictions: Prior research (Caldwell, 1951; England, 1955; Petersilia, 1985; Vito, 1986) reports that a significant relationship exists between offenders who have previously been convicted of criminal activities and their likelihood of recidivism.

Drug Abuse History: Given this large percentage (49.7 percent) of drug abusers in the sample and previous research findings (e.g. Benedict and Huff-Corzine, 1997; Caldwell, 1951; Clark *et al.*, 1988; Pritchard ,1979), drug abuse history may be a significant indicator of recidivism.

Supervision Level: The supervision level probationers were on during their probation term may contribute to a probationer's incentive to recidivate.

Type of Crime Committed: The probationers in the sample are classified based on the type of crime committed that resulted in the probation sentence. Type of crime committed is reported as one of the high-risk factors by Irish (1989).

Employment History: A probationer's employment history is measured by the percentage of time he/she was employed during the 12 months prior to presentence investigation in the sample. It is argued that probationers with instable and low levels of employment have more idle time for criminal activities. Caldwell (1951) and Pritchard (1979) report that instability of employment significantly increases recidivism.

Probation term: Probation term in months ranges from 1 to 144 months in the sample. The most common sentences were either 36 or 60 months. The basic justification for the inclusion of this variable is that the longer an offender is on probation, the greater the likelihood he would be caught committing an additional felony offense. Furthermore, it can be assumed that a probationer with a longer sentence has generally committed a more serious offense and/or has had a longer history of criminal behavior.

Neighborhood Characteristics: The neighborhood variables considered as potential explanatory variables are: jurisdiction population, percent persons over age 25 with 4 or more years college, percent persons over age 25 with 12 or more years schooling, unemployment rate, percent persons below poverty level, percent owner-occupied housing units, percent non-White population, percent Hispanic population, percent female-headed households with children under age 18, percent Republican votes cast for the president, percent property taxes and serious violent crime per capita.

6 Findings

BMA is implemented using "bic.surv" software by Chris T. Volinsky (available at http://www.research.att.com/∼ volinsky/software/bic.surv). The empirical findings for the whole sample, and the samples of Males, Females, Blacks, Whites and Hispanics are summarized in Table A.1 in Appendix. Reported are the posterior probabilities that the coefficients are non-zero for the variables included in the analysis and their standard deviations across completed data sets, and the posterior parameter estimates (means) and the standard deviations.

Following Rubin (1987), the posterior parameter estimates and probabilities that coefficients are non-zero are calculated by averaging over the individual estimates from the BMA analysis of each completed data set. The variance of a posterior parameter estimate, on the other hand, is the average of the estimated posterior variances from within each completed data set, plus the sample variance in the posterior parameter estimates across the completed data sets (multiplied by a factor that corrects for bias because the number of completed data sets is finite). Hence, the reported standard deviations for the posterior parameter estimates reflect not only model uncertainty, but also uncertainty due to missing data.

The results strongly support that social interactions contribute significantly to recidivism among all gender, ethnicity and race groups. Among other significant factors are: being male, being young, lack of employment, having a drug abuse history and prior felony convictions, and living in neighborhoods with high serious violent crime per capita for Blacks; being male, being young, lack of employment, having a drug abuse history and prior felony convictions, being convicted of a property offense, robbery or drug trafficking, and living in Republican neighborhoods for Whites; being young, lack of employment, having a drug abuse history and being convicted of a property offense, robbery or drug trafficking for Hispanics; lack of employment, having prior felony convictions and being under stringent supervision during probation for Females; being young, lack of employment and education, having a drug abuse history and prior felony convictions, and living in neighborhoods with low percentages of persons below poverty level for Males.

A separate analysis of recidivism for each gender, race and ethnicity group proves to be fruitful. Though, each group shares some common risk factors, there are also important differences. This is intuitive as each social group may be subjected to different opportunity sets. Becker (1971), for example, notes the structural discrimination minorities face in the marketplace. In the context of criminal behavior, a criminal record would double the "stigma" a minority person carries further dissipating the market opportunities and thereby increasing the likelihood of a repeat offense.

The evidence from the data is inconclusive for some variables as to their effects on recidivism. Among these are: probation term, ethnicity and age for Females; percent Republican votes cast for the president in the jurisdiction for Males; prior felony convictions, and percent persons with 4 or more years of college and the mean rearrest time among recidivists in the jurisdiction for Hispanics; percent Hispanic population in the jurisdiction for Whites; and marital status, education and probation term for Blacks.

This does not necessarily mean, however, that these variables could be safely discarded. In fact, they *must* be included in any prediction with weights proportional to their posterior probabilities. Based on posterior probabilities a distinction can be made which is otherwise not possible with P-values: a failure to reject the null hypothesis of "no effect" can be either because of a lack of sufficient data to detect an effect, or because the data may simply provide evidence *for* the null hypothesis. A posterior probability indicating "no effect" can be construed as an approximation to the posterior probability of the effect being "small", namely $P(|\theta| < \epsilon)$ provided that ϵ is at most about one half of the standard error (Berger and Delampady, 1987).

Section 6.1 investigates the robustness of these findings. Specifically, to ensure that there are no significant unobserved factors commonly shared by all probationers within jurisdictions that might have given rise to the covariation in their times to recidivate, a gamma frailty is introduced with a unit mean and an unknown variance. Consequently, if the variance vanishes, then the frailty is identically one for all neighborhoods indicating no unobserved neighborhood-level heterogeneity in the model. Next, for each sample the BMA analysis is repeated which has indicated, in all cases, a frailty variance that is almost zero. Thus, there does not exist any significant heterogeneity at the jurisdiction level that is not accounted for by the model. Consequently, the coefficient estimates and the posterior probabilities remain nearly the same.

To conclude the analysis in this section, BMA is compared with competing methods on the basis of evaluation of the risk factors for recidivism and risk assessment for potential recidivists. The predictive performance of BMA is tested with the sample for Blacks. The test results show that BMA predicts the risk for recidivism 10.39% more effectively than a method which picks the model based on the highest posterior model probability and 4.88% more effectively than a stepwise method. The performance of BMA in evaluating the risk factors is tested with the sample for Hispanics. The stepwise method is found in general to overstate the evidence for an effect in comparison with BMA.

The Whole Sample

Posterior probabilities for sex, employment history, education, drug abuse history, prior felony convictions, age, race, ethnicity, type of offense resulted in the probation sentence, probation term, supervision level, percent Hispanic population and percent persons below poverty level in the jurisdiction, and social interactions, as measured by the percent recidivists in the jurisdiction and the mean time to rearrest among them, indicate strong influences on recidivism.

The risk of recidivism among Females is lower than that of Males. Having at least a high school degree or GED reduces the likelihood of recidivism, so does a higher percentage of time employed prior to probation.

More intensive drug abuse increases the risk of a repeat offense. One possible explanation for this finding is that a probationer with a drug abuse history would possibly remain engaged in criminal activities if only to feed the drug habit. Notice also that probationers with prior felony convictions are at a higher risk of recidivating, all else being the same.

The age of an offender matters: the younger probationers are more likely to recidivate than the older. Also important are the ethnic and racial background of the probationers. As such, while Blacks and American Indians/Pacific Islanders are more likely to recidivate than Whites, Hispanics are at a higher risk than all non-Hispanics. As for the type of offense resulted in the probation sentence, probationers sentenced for property offenses (burglary, larceny and auto theft), robbery and drug trafficking are at a higher risk of recidivating than those convicted of murder or nonnegligent manslaughter.

A shorter probation term increases the likelihood of recidivism. This finding is surprising as those who were given longer sentences have generally committed more serious offenses and/or have a longer history of criminal behavior. One possible explanation for this finding is that short sentences do not deter further criminal activity. That is, probationers who receive light sentences may rationalize that the benefits of future crimes outweigh the potential costs. Moreover, they may have less time to serve if reconvicted. More surprisingly, a more strict supervision level indicates a higher risk of recidivism. One possible explanation for this finding is that probationers who are under more stringent supervision are supervised more closely and have fewer opportunities for criminal activity without detection. Also, they possibly are more serious and habit offenders.

Interestingly, a higher percentage persons below poverty level, which can be considered as a measure of economic well being in the neighborhood, decreases the chances of a repeat offense. This could be possibly due to the lower propensity to commit property offenses among the probationers. Also note that, there is strong evidence for the effect of percent Hispanic population in the jurisdiction. An increase in percent Hispanic population in the neighborhood slightly increases the risk of recidivism. Furthermore, though the data indicate evidence against an effect for the percent Republican votes cast for the president and violent serious crime per capita in the jurisdiction, the evidence is weak.

Finally, social interactions as measured by the percent recidivists in the neighborhood and the mean time to rearrest among them, are significant. The higher the percentage of probationers who recidivate in the jurisdiction of a probationer (the lower the mean time to rearrest among them), the higher will be the risk of recidivism for the probationer.

Males

The results when only the male probationers are considered, replicate closely those for the overall sample. This is probably due to the over-representation of Males in the sample. The variables for which the BMA analysis indicates strong evidence for an effect for the whole sample (except sex of course) are also relevant for Males, with slightly lower posterior probabilities for probation term and percent persons below poverty level in the jurisdiction, and a slightly higher posterior probability for the mean rearrest time among recidivists in the jurisdiction.

Females

The female offenders make up a much smaller proportion of the correctional population than the male offenders. For example, only 22 percent of the adults on probation were women during 2001. As a result, research on the recidivism by the female offenders has been lacking as compared with the males. However, those risk factors which can successfully assess the risk of recidivism among the male probationers may fail to do so for the females. Hence, a separate analysis of recidivist behavior among female probationers is of interest.

The posterior probabilities for employment history, prior felony convictions, type of offense resulted in the probation sentence, supervision level, and social interactions, as measured by the percentage of recidivists in the jurisdiction, indicate strong evidences for an effect on the female recidivism. Moreover, the effect of each of these variables is stronger compared to the whole sample and Males. The female probationers who are put on more strict supervision, convicted of property offenses, robbery and drug trafficking, were employed for a lower percentage of time prior to probation sentence, and live in jurisdictions with high percentages of recidivists are more likely to recidivate. As different from the whole sample and Males, the evidence is against an effect of the mean rearrest time among recidivists in the jurisdiction on recidivism. That is, for Females, not how quickly the probationers in their neighborhood recidivate but their number matters. Furthermore, the relation of employment history to recidivism is different from the whole sample and Males. Though, female probationers who were employed 40% or more of the time prior to probation are less likely to recidivate than those who were employed under 40% of the time, the risk of recidivism is lower for those who were employed between 40%-60% of the time than it is for those who were employed over 60%.

Note also that the posterior probability for drug abuse history indicates weak evidence for an effect; more intensive drug abuse increases the risk of recidivism. Finally, the evidence is against but weak for age, ethnicity, probation term, and percent female-headed households, percent persons with 4 or more years of college education and percent persons below poverty level in the jurisdiction. The indecisiveness of the data is probably because Females make up only 13.6% of the original sample. Though the findings indicate (weak) against evidence for the age variable, its relation to recidivism, as employment history, is different from the whole sample and Males. Female probationers 20 and over years of age are less likely to recidivate than those under 20 years of age, but the risk of recidivism for those between ages 25-29 is higher than it is for those between ages 20 and 24, and ages 30 and above.

Whites

I analyze recidivism among Whites and Blacks separately. Because of their small representation, less than 4 percent of the original sample, I do not separately consider American Indians, Alaskan Natives, Asians, Pacific Islanders and other races.

The BMA analysis of the sample of Whites provides strong evidence for an effect for sex, employment history, prior felony convictions, drug abuse history, age, ethnicity, type of offense resulted in the probation sentence, supervision level, percent persons below poverty level in the jurisdiction and social interactions, as measured by the percent recidivists in the jurisdiction. The interpretations are similar to the whole sample, with percent recidivists in the jurisdiction having a higher effect on the recidivism of Whites compared to Males, Females and the whole sample. As different from the whole sample and Males and similar to Females, the evidence is against an effect of the mean rearrest time among recidivists in the jurisdiction on recidivism.

Furthermore, the posterior probability indicates positive evidence for an effect of percent Republican votes cast for the president in the jurisdiction. An increase in the percentage of Republican votes increases the risk of recidivism of Whites, albeight slightly. Also note that the evidence is weak for an effect of education and probation term on recidivism. Probationers with at least *some* high school education are less likely to recidivate, so do probationers with longer probation sentences. Finally, the evidence is against but weak for percent Hispanic population in the jurisdiction.

Blacks

The BMA analysis points to positive evidence for an effect for sex, employment history, prior felony convictions, drug abuse history, age, type of offense resulted in the probation sentence, supervision level, serious violent crime per capita in the jurisdiction and social interactions, as measured by the percent recidivists in the jurisdiction and the mean time to rearrest among them.

The interpretations are similar to the whole sample, with percent recidivists in the jurisdiction having a lower effect compared to all other samples, and the mean rearrest time among recidivists variable having a higher effect compared to Males and the whole sample. Also, as opposed to all other samples, the evidence is strong for serious violent crime per capita in the jurisdiction. An increase in per capita violent serious crime substantially decreases the risk of recidivism. Considering the high number of Blacks arrested, convicted and consequently sentenced in the criminal justice system, the police might become more strict as serious violent crime increases, increasing the chance of being arrested.

The evidence is weak for percent Hispanic population and percent persons below poverty level in the jurisdiction, and inconclusive for marital status, education, probation term, jurisdiction population, and percent female-headed households and percent persons with 4 or more years of college in the jurisdiction.

Hispanics

The only other study in the literature which separately examines recidivism among Hispanic probationers is Benedict and Huff-Corzine 1997. Unfortunately, however, the model used in their study is not statistically significant. Hence, any significant results as to the factors that contribute to recidivism among Hispanic felony probationers are of additional interest.

The BMA analysis suggests positive evidence for an effect for employment and drug abuse histories, age, type of offense resulted in the probation sentence, supervision level, percent owner-occupied housing in the jurisdiction and social interactions, as measured by the percent recidivists in the jurisdiction. The interpretations are similar to the whole sample. Similar to Females and Whites, the evidence is against for an effect of the mean rearrest time among recidivists. However, as opposed to Females and Whites, it is weak for Hispanics. Furthermore, the effect of percent recidivists on the recidivism of Hispanics is similar to that of Whites, quite a bit higher compared the whole sample, Males, Females and Blacks.

The evidence is weak for sex and prior felony convictions, and (weak) against for percent non-White population, percent female-headed households, percent persons with 12 or more years of schooling, percent persons below poverty level and serious violent crime per capita in the jurisdiction, probation term and the mean rearrest time among recidivists in the jurisdiction. The lack of conclusive evidence can perhaps be attributed to the fact that Hispanics make up only 22% of the original sample.

6.1 Robustness

There could be sources of jurisdiction-level heterogeneity affecting the variability in observed times to recidivism that might not have been captured with the covariates used in the analysis in the previous section. Excess risk or *frailty* for distinct neighborhoods over and above any measured covariates is known as *overdispersion.* Hence, if an overdispersion existed due to unobserved and/or omitted factors shared by probationers within jurisdictions, and yet neglected, the effect of social interactions on recidivism might have been overstated.

Overdispersion can be handled with a frailty model. A frailty model attempts to measure the overdispersion by representing it as an unobservable multiplicative effect on the hazard, or frailty. That is, the hazard for probationer i becomes

$$\begin{aligned}\lambda(t, \mathbf{x}_i, \mathbf{y}_{n(i)}, \mathbf{m}^e_{n(i)}|\bar{\xi}_j) &= \bar{\xi}_j \lambda(t, \mathbf{x}_i, \mathbf{y}_{n(i)}, \mathbf{m}^e_{n(i)}) \\ &= \bar{\xi}_j \lambda_0(t) \text{exp}(\alpha' \mathbf{x}_i + \beta' \mathbf{y}_{n(i)} + J' \mathbf{m}^e_{n(i)})\end{aligned} \tag{6.1}$$

where $\bar{\xi}_j$ is a random variable representing the unobserved heterogeneity specific to probationer i's jurisdiction, $j = n(i)$, that is assumed to be independent of the covariates. Hence, from a proportional hazard perspective, it is easy to see how $\bar{\xi}_j$ may correspond to an omitted covariate (or set of covariates). A log-likelihood is obtained by conditioning on the unobserved $\bar{\xi}$ and then integrating over its distribution.

To check the robustness of the results reported in the previous section, frailty is assumed to follow a gamma distribution with density function, $f(\bar{\xi}_j) = \delta^\delta \bar{\xi}_j^{\delta-1} / \Gamma(\delta)$, where δ is the scale parameter and the distribution is normalized to have a unit mean and variance $1/\delta = \phi$ is left unspecified for the purposes of identifiability. This also leads to a nice interpretation: when the variance vanishes, the frailty is identically one for all the neighborhoods and there is no heterogeneity in the model.

The gamma distribution is a commonly used and convenient heterogeneity distribution as it gives a closed form expression for the log-likelihood, avoiding numerical integration. Nonparametrically modelling frailty with a discrete mixing distribution is an alternative approach. Even if the distribution of $\bar{\xi}_j$ is unknown, the parameters can be consistently estimated using an extension of the Heckman and Singer (1984) approach (Meyer, 1990). However, as reported in Meyer (1990), this increases the computational burden. Furthermore, Guo and Rodriguez (1992) find that when combined with a flexible form of the baseline hazard, there is little to favor the nonparametric approach over the parametric approach.

If $\bar{\xi}$'s are viewed as missing data, the unobserved heterogeneity can be tackled with an EM algorithm. However, the EM algorithm is relatively slow, and the variance estimates require further computation. The results reported in this section are obtained using the penalized partial log-likelihood approach. The details of the penalized partial log-likelihood approach and its connection to the EM algorithm are extensively studied in Therneau *et al.* (2000), and will not be repeated here.

Therneau *et al.* (2000) show that maximizing the penalized partial log-likelihood,

$$PPL = L_1(\alpha, \beta, J, \xi; \text{data}) - g(\xi; \phi) \tag{6.2}$$

over α, β, J and ξ coincides with the EM solution for any fixed value of ϕ. Here the penalty function is given by $g(\xi, \phi) = -1/\phi \sum_{j=1}^{q}[\xi_j - \exp(\xi_j)]$, where q is the number of neighborhoods and $\xi_j = log(\bar{\xi}_j)$. L_1 is the log of the usual Cox partial likelihood developed from an alternative version of the hazard which is equivalent to Eq. (6.1),

$$\lambda(t, \mathbf{x}_i, \mathbf{y}_{n(i)}, \mathbf{m}^e_{n(i)}|\xi_j) = \lambda_0(t)\exp(\alpha'\mathbf{x}_i + \beta'\mathbf{y}_{n(i)} + J'\mathbf{m}^e_{n(i)} + B_i\xi) \tag{6.3}$$

where B is matrix of q indicator variables such that $B_{ij} = 1$ when subject i is a member of neighborhood j and 0 otherwise, and each individual belongs to only one neighborhood.

Using the penalized partial log-likelihood approach, the BMA is applied to each completed data set of each sample for the selection of potential covariates employed in the previous section as before. Table 6.1.1 reports the estimated variance in frailty for each sample. The reported variances are obtained by taking the average of the weighted average (with posterior model probabilities as weights) of the BMA estimated variances in frailty over the completed data sets.

As can be observed from Table 6.1.1, the estimated variances in frailty are very small for all samples. These results imply that overdispersion due to unobserved/omitted covariates is negligible. That is, the observed variables taken into account are sufficient to explain the variability in times to recidivism across jurisdictions. Furthermore, since overdispersion is very small, the values of the posterior parameter estimates, the standard deviations and the probabilities that the coefficients are non-zero for each sample are very similar to their values in the previous section. Thus, the findings in the previous section prove to be robust.

Sample	*Estimated variance in frailty*
Whole sample	0.0050
Females	0.0045
Males	0.0050
Blacks	0.0048
Whites	0.0043
Hispanics	0.0044

Table 6.1.1: Estimated variance in frailty

6.2 Comparison with Stepwise Methods: Evaluation of the Risk Factors and Predictive Performance

Table 6.2.1 reports the performances BMA and stepwise model selection method in evaluating the risk factors using one of the completed data sets for Hispanics for comparison. With the stepwise method, it is not obvious how to obtain the P-values when the completed data sets result in different models. Hence, only one of the completed data sets is used to demonstrate the differences between the two approaches. Hispanics are chosen since, as reported in the previous section, Hispanic sample is one of the samples for which BMA analysis indicates indecisiveness for many variables.

For percent recidivists in the jurisdiction, employment history, drug abuse history, prior felony convictions, age, type of crime committed and supervision level, P-values and posterior probabilities agree in saying that there is strong evidence for an effect. For the remaining variables chosen by the stepwise method, however, two approaches lead to qualitatively different conclusions. For sex and percent owner-occupied housing in the jurisdiction, posterior probabilities indicate weak evidence for an effect, but the P-values would lead to the effect being "highly significant" ($P < 0.01$). For female-headed households and mean rearrest time among recidivists in the jurisdiction, posterior probabilities indicate (weak) evidence against an effect. However, the P-values again overstate the evidence for an effect, leading the effect being called "highly significant" for mean rearrest time and "significant" ($P < 0.05$) for percent female-headed households. Furthermore, for percent persons with 12 years or more schooling and percent persons below poverty level in the jurisdiction, posterior probabilities indicate against evidence. The P-values on the other hand, would lead to the effect being called "significant" for percent persons with 12 years or more schooling and "highly significant" for percent persons below poverty level.

Variable	*P-value*	*$P(\theta \neq 0)$*
Sex	0.0092	59.4
Employment history	0.0001	98.2
Drug abuse history	0.0000	100
Prior felony convictions	0.0000	100
Age	0.0000	100
Type of crime committed	0.0000	100
Supervision level	0.0000	100
Percent female-headed households	0.0277	25.2
Percent persons with 12 or more years of schooling	0.0161	0.5
Percent persons below poverty level	0.0099	4
Percent owner-occupied housing	0.0000	54.3
Mean rearrest time	0.0030	29.9
Percent Recidivists	0.0000	100

Table 6.2.1: P-values for the stepwise chosen model and the corresponding posterior probabilities with BMA for one of the completed data sets for Blacks

Next, I test the predictive performance of BMA procedure using one of the completed samples for Blacks. Black sample is chosen as it is another sample for which BMA analysis indicate indecisiveness for many variables. First, the sample is randomly split into two such that an equal number of events (1020 rearrests) occurred in each. Then, the results from the BMA analysis are compared with those from a single model selected by a stepwise procedure and the model with the highest posterior probability. This is repeated for ten random splits of the sample. The PPS for the competing methods and their standard deviations across different splits are shown in Table 6.2.2; a higher score (less negative) indicates better predictive performance. The difference in PPS of 100.83 can be viewed as an increase in predictive performance *per event* by a factor of exp(100.83/1020)=1.1039 or by about 10.39%. This means that BMA predicts who is at risk for recidivism 10.39% more effectively than a method which picks the model with the best posterior model probability and 4.88% more effectively than a stepwise method.

Method	*PPS*
Top Model	-6914.33 (28.91)
Stepwise	-6862.14 (27.06)
BMA	-6813.50 (22.30)

Table 6.2.2: PPSs for the model with the highest posterior probability, the stepwise chosen model and BMA

7 Conclusions

Using a national sample, this paper has identified the potential risk factors for recidivism among Female, Male, Black, White and Hispanic felony probationers. Social interactions are embedded in a Cox proportional hazard model to model recidivism. To cope with model uncertainty, Bayesian model averaging is used for the selection of covariates and the subsequent inference. To check for unobserved neighborhood-level heterogeneity, a frailty parameter is introduced into the model. The empirical results remain robust under frailty thus indicating no significant overdispersion.

The empirical analysis in this study point to social interactions as one of the most significant contributor to recidivism among all gender, ethnicity and race groups. A separate analysis of recidivism for each gender, race and ethnicity group proves to be fruitful. Though, each group shares some common risk factors, there are also important differences. Among other significant factors are: being male, being young, lack of employment, having a drug abuse history and prior felony convictions, and living in neighborhoods with high serious violent crime per capita for Blacks; being male, being young, lack of employment, having a drug abuse history and prior felony convictions, being convicted of a property offense, robbery or drug trafficking, and living in Republican neighborhoods for Whites; being young, lack of employment, having a drug abuse history and being convicted of a property offense, robbery or drug trafficking for Hispanics; lack of employment, having prior felony convictions and being under stringent supervision during probation for Females; being young, lack of employment and education, having a drug abuse history and prior felony convictions, and living in neighborhoods with low percentages of persons below poverty level for Males.

The evidence from the data is inconclusive as to the effects of some variables on recidivism. Among these are: probation term, ethnicity and age for Females; percent Republican votes cast for the president in the jurisdiction for Males; prior felony convictions, and percent persons with 4 or more years of college and the mean rearrest time among recidivists in the jurisdiction for Hispanics; percent Hispanic population in the jurisdiction for Whites; and marital status, education and probation term for Blacks. This does not necessarily mean, however, that these variables could be safely neglected in any future work. In fact, they should be included in any prediction with weights proportional to their posterior probabilities.

Methodologically, Bayesian model averaging is shown to lead to a better evaluation of the risk factors, as well as improved risk assessment for potential recidivists compared to traditional analysis which typically identifies risk factors using stepwise methods.

References

[1] Amemiya, T. (1985). *Advanced Econometrics.* Cambridge: Harvard University Press.

[2] Becker, G. A. (1971). *The Economics of Discrimination.* Chicago: University of Chicago Press.

[3] Benedict, W. R., and L. Huff-Corzine (1997). Return to the Scene of Punishment: Recidivism of Adult Male Property Offenders on Felony Probation, 1986-1989. *Journal of Research in Crime and Delinquency* 34 (2), 237-252.

[4] Berger, J. O. and M. Delampady (1987). Testing Precise Hypotheses. *Statistical Science* 2, 317-352.

[5] Breslow, N. (1975). Analysis of Survival Data under the Proportional Hazards Model. *International Statistical Review* 43, 45-48.

[6] Brock, W. and S. Durlauf (2001a). Interactions-based Models. In J. J. Heckman and E. Leamer (Eds.), *Handbook of Econometrics,* Elsevier Science. Vol.5, Ch.54, p.3297-3380.

[7] Brock, W. and S. Durlauf (2001b). Discrete Choice with Social Interactions. *The Review of Economic Studies* 68 (2), 235-260.

[8] Caldwell, M. G. (1951). Review of a New Type of Probation Study Made in Alabama. *Federal Probation* 15, 3-11.

[9] Chatfield, C. (1995). Model Uncertainty, Data mining, and Statistical Inference (with discussion). *Journal of the Royal Statistical Society. Series A* 158, 419-466.

[10] Clarke, S. H., Y. W. Lin, and W. L. Wallace (1988). *Probationer Recidivism in North Carolina: Measurement and Classification of Risk.* Chapel Hill: University of North Carolina, Institute of Government.

[11] Cox, D. R. (1972). Regression Models and Life Tables. *Journal of the Royal Statistics Society. Series B* 34: 187-202.

[12] Draper, D. (1995). Assessment and Propagation of Model Uncertainty. *Journal of the Royal Statistics Society. Series B* 57, 45-97.

[13] Efroymson, M. (1960). Multiple Regression Analysis. In A. Ralston and H. Wilf (Eds.), *Mathematical Methods for Digital Computers.* New York: Wiley.

[14] England, R. W. (1955). A Study of Postprobation Recidivism among Five Hundred Federal Offenders. *Federal Probation* 19, 10-16.

[15] Freeman. S., J. Grogger and J. Sonstelie (1996). The Spatial Concentration of Crime. *Journal of Urban Economics* 40 (2), 216-31.

[16] Furnival, G. M. and R. W. Wilson (1974). Regression by Leaps and Bounds. *Technometrics* 16, 499-511.

[17] Glaeser, D.L., B. Sacerdote and J.A. Scheinkman (1996). Crime and Social Interactions. *Quarterly Journal of Economics* 445, 507-548.

[18] Good, I. J. (1952). Rational decisions. *Journal of the Royal Statistics Society. Series B* 14, 107-114.

[19] Guo, G. and G. Rodriguez, (1992). Estimating a Multivariate Proportional Hazards Model for Clustered Data Using the EM Algorithm, With an Application to Child Survival in Guatemala. *Journal of the American Statistical Association*, 87, 969-976.

[20] Heckman J. and B. Singer, (1984). A Method for Minimizing the Distributional Assumptions in Econometric Models for Duration Data. *Econometrica* 52, 271-320.

[21] Honaker, J., A. Joseph, G. King, and K. Scheve (2001). *A Program for Missing Data (Gauss Version).* Cambridge, MA: Harvard University, http://GKing.Harvard.edu/.

[22] Irish, J. E. (1989). *Probation and Recidivism: A Study of Probation Adjustment and Its Relationship to Post-Probation Outcome for Adult Criminal Offenders.* Mineola, NY: Nassau County Probation Department.

[23] Kass, R. E. and A. E. Raftery (1995). Bayes factors. *Journal of the American Statistical Association* 90, 773-795.

[24] King, G., J. Honaker, A. Joseph, and K. Scheve (2001). Analyzing Incomplete Political Science Data: An Alternative Algorithm for Multiple Impuation. *American Political Science Review* 95(1), 49-69.

[25] Kuk, A. Y. C. (1984). All Subsets Regression in a Proportional Hazards Model. *Biometrika* 71, 587-592.

[26] LaFree, G. D. (1985). Official Reactions to Hispanic Defendants in the Southwest. *Journal of Research in Crime and Delinquency* 22, 213-37.

[27] Landis, J. R., J. K. Mercer, and C. E. Wolff (1969). Success and Failure of Adult Probationers in California. *Journal of Research in Crime and Delinquency* 6,34-40.

[28] Lawless, J. and K. Singhal (1978). Efficient Screening of Nonnormal Regression Models. *Biometrics* 34, 318-327.

[29] Madigan, D. and A. E. Raftery (1994). Model Selection and Accounting for Model Uncertainty in Graphical Models using Occam's Window. *Journal of the American Statistical Association* 89, 1535-1546.

[30] Madigan, D., S. A. Andersson, M. Perlman, and C. T. Volinsky (1996). Bayesian Model Averaging and Model Selection for Markov Equivalence Classes of Acyclic Digraphs. *Communications in Statistics, Theory and Methods* 25, 2493-2520.

[31] Maltz, M. D. (1984). *Recidivism.* Orlando, FL: Academic Press.

[32] Mandel, J. (1979). Hispanics in the Criminal Justice System-The Nonexistent Problem. *Law and Justice* 3, 16-20.

[33] Manski, C. (1995). *Identification Problems in Social Sciences.* Cambridge: Harvard University Press.

[34] McGaha, J., M. Fichter, and P. Hirschburg (1987). Felony Probation: A Re-examination of Public Risk. *American Journal of Criminal Justice* 11, 1-9.

[35] Meyer, B. D., (1990). Unemployment Insurance and Unemployment Spells. *Econometrica* 58, 757-782.

[36] Petersilia, J. (1985). *Probation and Felony Offenders.* Washington, DC: U.S. Department of Justice.

[37] Petersilia, J., S. Turner, J.Kahan, J. Peterson (1985). *Exexutive Summary of Rand's Study, "Granting Felons Probation: Public Risks and Alternatives". Crime and Delinquency* 31, 379-392.

[38] Petersilia, J. and S. Turner (1990). Comparing Intensive and Regular Supervision for High-Risk Probationers: Early Results from an Experiment in California. *Crime and Delinquency* 36, 87-111.

[39] Pritchard, D. A. (1979). Stable Predictors of Recidivism: A Summary. *Criminology* 17, 15-21.

[40] Raftery, A. E., D. Madigan, and J. Hoeting (1993). Model Selection and Accounting for Model Uncertainty in Linear Regression Models. *Technical Report* 262, University of Washington, Seattle.

[41] Raftery, A. E., D. Madigan, and J. Hoeting (1997). Bayesian Model Averaging for Linear Regression Models. *Journal of the American Statistical Association*, 92, 179-191.

[42] Raftery, A. E. (1996). Approximate Bayes Factors and Accounting for Model Uncertainty in Generalised Linear Models. *Biometrika* 83, 251-266.

[43] Rubin, D.B. (1987). *Multiple Imputation for Nonresponse in Surveys.* J. Wiley & Sons, New York.

[44] Sah, R. (1991). Social Osmosis and Patterns of Crime. *Journal of Political Economy*, 99, 1272-1295.

[45] Shinnar, R. and S. Shinnar (1975). The Effects of the Criminal Justice System on the Control of Crime: A Quantitative Approach. *Law and Society Review* 9, 581-611.

[46] Unnever, J. D. (1981). Institutional Racism: Direct and Structural Discrimination. *Presented at the 76th Annual Meeting of the American Sociological Association,* Toronto, Ontario.

[47] Therneau, T. M., P. M. Grambsch and V. S. Pankratz, (2000). Penalized Survival Models and Frailty. *Technical Report* 66, Department of Health Science Research, Mayo Clinic, Rochester, Minnesota.

[48] Visher, C. A., P. K. Lattimore, and R. L. Linster (1991). Predicting the Recidivism of Serious Youthful Offenders Using Survival Models. *Criminology* 29, 329-66.

[49] Vito, G. F. (1986). Felony Probation and Recidivism: Replication and Response. *Federal Probation* 50, 17-25.

[50] Volinsky, C. (1997). Bayesian Model Averaging for Censored Survival Models. *University of Washington Statistics Department Ph.D. Dissertation.*

[51] Volinsky, C. T., D. Madigan, A. E. Raftery, and R. A. Kronmal (1997). Bayesian Model Avereging in Proportional Hazard Models: Assessing the Risk of a Stroke. *Applied Statistics* 46, 433-448.

[52] Whitehead, J. T. (1991). The Effectiveness of Felony Probation: Results from an Eastern State. *Justice Quarterly* 8, 525-43.

Appendix: The following table displays 1) (in bold) the posterior probabilities that the coefficients are non-zero and their standard deviations (in parenthesis) across completed data sets; 2) the posterior parameter estimates and standard deviations (in parentheses)

	Whole Sample	*Males*	*Females*	*Whites*	*Blacks*	*Hispanics*
Sex	**100 (0.00)**			**100 (0.00)**	**100 (0.00)**	**68.06 (25.99)**
Male						
Female	-0.482 (0.058)			-0.392 (0.078)	-0.601 (0.086)	-0.224 (0.198)
Employment history	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**99 (2.24)**	**93.56 (13.42)**
Under 40%						
40%-60%	-0.105 (0.046)	-0.074 (0.054)	-0.527 (0.201)	-0.134 (0.079)	-0.075 (0.083)	-0.128 (0.098)
60% or more	-0.328 (0.057)	-0.323 (0.063)	-0.456 (0.133)	-0.367 (0.076)	-0.274 (0.076)	-0.331 (0.133)
Marital status	**4.26 (5.84)**	**7.34 (10.06)**	**0 (0.00)**	**0 (0.00)**	**23.88 (42.89)**	**0 (0.00)**
Married/Widower						
Divorced/Separated	-0.002 (0.014)	-0.004 (0.021)	0.000 (0.000)	0.000 (0.000)	-0.010 (0.051)	0.000 (0.000)
Single	0.005 (0.025)	0.009 (0.035)	0.000 (0.000)	0.000 (0.000)	0.059 (0.133)	0.000 (0.000)
Education	**100 (0.00)**	**100 (0.00)**	**0.44 (0.98)**	**60 (54.77)**	**20 (44.72)**	**0.00 (0.00)**
Grade school						
Some high school	0.057 (0.066)	0.075 (0.069)	-0.000 (0.013)	-0.010 (0.080)	0.037 (0.103)	0.000 (0.000)
High school (GED)	-0.086 (0.076)	-0.074 (0.078)	-0.001 (0.022)	-0.084 (0.118)	0.004 (0.052)	0.000 (0.000)
Some college	-0.188 (0.076)	-0.163 (0.080)	-0.002 (0.034)	-0.157 (0.175)	-0.036 (0.106)	0.000 (0.000)
College	-0.301 (0.148)	-0.236 (0.156)	-0.003 (0.058)	-0.313 (0.363)	0.009 (0.085)	0.000 (0.000)
Drug abuse history	**100 (0.00)**	**100 (0.00)**	**65.80 (47.70)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**
No abuse						
Occasional abuse	0.096 (0.049)	0.085 (0.050)	0.145 (0.205)	0.146 (0.078)	0.072 (0.061)	0.135 (0.086)
Frequent abuse	0.335 (0.044)	0.328 (0.042)	0.294 (0.289)	0.394 (0.074)	0.315 (0.077)	0.453 (0.100)
Prior felony convictions	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**49.78 (46.01)**
None						
One	0.275 (0.047)	0.262 (0.049)	0.415 (0.140)	0.256 (0.072)	0.285 (0.073)	0.143 (0.184)
Two or more	0.346 (0.056)	0.322 (0.054)	0.591 (0.205)	0.420 (0.068)	0.248 (0.083)	0.159 (0.203)
Age	**100 (0.00)**	**100 (0.00)**	**19.56 (43.74)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**
Under 20						
20-24 years old	-0.251 (0.049)	-0.254 (0.050)	-0.046 (0.141)	-0.245 (0.070)	-0.298 (0.076)	-0.252 (0.104)
25-29 years old	-0.352 (0.052)	-0.384 (0.055)	-0.012 (0.090)	-0.260 (0.079)	-0.501 (0.092)	-0.299 (0.112)
30-39 years old	-0.501 (0.062)	-0.520 (0.068)	-0.074 (0.201)	-0.385 (0.078)	-0.696 (0.129)	-0.428 (0.118)
40-49 years old	-0.823 (0.083)	-0.850 (0.090)	-0.143 (0.374)	-0.665 (0.124)	-1.095 (0.150)	-0.637 (0.170)
50 and older	-1.331 (0.134)	-1.364 (0.139)	-0.238 (0.622)	-1.263 (0.193)	-1.321 (0.209)	-1.191 (0.329)
Race	**100 (0.00)**	**100 (0.00)**	**0 (0.00)**			**0 (0.00)**
White						
Black	0.495 (0.039)	0.520 (0.042)	0.000 (0.000)			0.000 (0.000)
Amer.Indian/ Pac. Islander	0.119 (0.161)	0.135 (0.179)	0.000 (0.000)			0.000 (0.000)
Asian/ Alaskan Native	-0.114 (0.130)	-0.126 (0.136)	0.000 (0.000)			0.000 (0.000)
Other	0.096 (0.172)	0.118 (0.176)	0.000 (0.000)			0.000 (0.000)
Type of crime committed	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**
Murder/nonneg manslaughter						
Rape	-0.246 (0.178)	-0.338 (0.194)	-0.297 (0.808)	0.080 (0.292)	-0.347 (0.263)	0.066 (0.436)
Robbery	0.568 (0.168)	0.452 (0.185)	1.487 (0.421)	0.901 (0.283)	0.406 (0.251)	1.024 (0.437)
Aggravated assault	0.267 (0.169)	0.181 (0.188)	0.788 (0.417)	0.683 (0.287)	0.140 (0.247)	0.740 (0.423)
Burglary	0.674 (0.166)	0.572 (0.184)	1.418 (0.443)	1.124 (0.280)	0.464 (0.248)	1.137 (0.431)
Larceny/auto theft	0.621 (0.166)	0.553 (0.184)	0.951 (0.423)	1.004 (0.278)	0.524 (0.245)	0.844 (0.425)
Drug trafficking	0.475 (0.166)	0.394 (0.183)	0.819 (0.442)	0.774 (0.278)	0.389 (0.235)	0.879 (0.418)
Other felony	0.553 (0.164)	0.468 (0.182)	1.047 (0.418)	1.000 (0.278)	0.365 (0.245)	1.027 (0.417)

(Table continued)

	Whole Sample	*Males*	*Females*	*Whites*	*Blacks*	*Hispanics*
Ethnicity	**100 (0.00)**	**100 (0.00)**	**32.30 (31.50)**	**100 (0.00)**	**0.36 (0.80)**	
Hispanic						
Non-hispanic	-0.207 (0.046)	-0.196 (0.049)	-0.100 (0.176)	-0.296 (0.069)	-0.001 (0.013)	
Probation term	**93.84 (7.96)**	**82.26 (12.87)**	**15.56 (7.16)**	**71.10 (11.14)**	**19.90 (13.68)**	**12.88 (11.89)**
	-0.003 (0.001)	-0.002 (0.001)	-0.001 (0.002)	-0.002 (0.002)	-0.001 (0.001)	-0.000 (0.001)
Supervision	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**
Administrative						
Minimum	-0.197 (0.088)	-0.195 (0.083)	-0.277 (0.249)	-0.233 (0.117)	-0.176 (0.136)	-0.215 (0.163)
Medium	0.161 (0.065)	0.147 (0.069)	0.259 (0.195)	0.132 (0.083)	0.192 (0.124)	0.145 (0.137)
Maximum	0.540 (0.074)	0.521 (0.078)	0.692 (0.205)	0.602 (0.096)	0.460 (0.125)	0.443 (0.155)
Intense	0.586 (0.091)	0.556 (0.095)	1.002 (0.235)	0.652 (0.117)	0.529 (0.148)	0.583 (0.141)
% Non-White	**0.34 (0.76)**	**0 (0.00)**	**0.80 (1.79)**	**0.52 (1.16)**	**5.76 (6.32)**	**14.32 (23.22)**
	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)	-0.000 (0.001)	0.000 (0.002)	-0.002 (0.005)
% Hispanic	**100 (0.00)**	**100 (0.00)**	**0 (0.00)**	**28.32 (28.40)**	**66.18 (26.37)**	**0.80 (1.10)**
	0.006 (0.001)	0.006 (0.001)	0.000 (0.000)	0.002 (0.003)	0.004 (0.004)	0.000 (0.000)
% Female headed households	**0 (0.00)**	**0.42 (0.94)**	**8.64 (11.83)**	**0 (0.00)**	**8.86 (6.17)**	**7.64 (10.82)**
	0.000 (0.000)	-0.000 (0.001)	-0.001 (0.006)	0.000 (0.000)	-0.001 (0.003)	-0.001 (0.005)
% w/ $\geq$ 12 years of school	**0 (0.00)**	**3.64 (3.76)**	**1.72 (2.55)**	**4.60 (10.29)**	**0.70 (0.97)**	**1.88 (1.67)**
	0.000 (0.000)	0.000 (0.003)	-0.000 (0.003)	0.001 (0.004)	0.000 (0.001)	0.000 (0.002)
% w/ $\geq$ 4 years of college	**0 (0.00)**	**0 (0.00)**	**9.20 (14.94)**	**1.02 (1.45)**	**6.14 (2.34)**	**38.92 (31.10)**
	0.000 (0.000)	0.000 (0.000)	0.002 (0.007)	0.000 (0.001)	0.001 (0.003)	0.006 (0.010)
% Below poverty level	**100 (0.00)**	**96.36 (3.76)**	**8.78 (9.67)**	**95.36 (10.38)**	**56.38 (32.07)**	**8.82 (13.03)**
	-0.024 (0.005)	-0.022 (0.007)	-0.002 (0.007)	-0.020 (0.007)	-0.012 (0.013)	-0.002 (0.009)
% Owner occupied housing	**0 (0.00)**	**0.90 (1.34)**	**0.66 (1.13)**	**0.46 (1.03)**	**0.90 (1.29)**	**81.54 (23.58)**
	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.001)	0.013 (0.008)
Unemployment rate	**6.14 (5.42)**	**0.54 (1.21)**	**0.42 (0.94)**	**0 (0.00)**	**3.54 (3.73)**	**0.40 (0.89)**
	0.002 (0.009)	0.000 (0.002)	0.000 (0.004)	0.000 (0.000)	0.002 (0.011)	-0.000 (0.004)
% Republican	**34.82 (9.07)**	**35.340 (9.58)**	**0.62 (1.00)**	**81.58 (28.38)**	**0.98 (1.03)**	**0.98 (1.38)**
	0.002 (0.003)	0.002 (0.003)	0.000 (0.000)	0.007 (0.005)	-0.000 (0.001)	0.000 (0.001)
Violent serious crime per capita	**40.66 (13.23)**	**53 (13.03)**	**1.24 (1.72)**	**0 (0.00)**	**98.92 (2.41)**	**9.84 (7.95)**
	-1.199 (1.612)	-1.816 (1.915)	-0.038 (0.544)	0.000 (0.000)	-6.534 (1.897)	0.518 (1.814)
% Property taxes	**3.20 (1.46)**	**1.18 (1.62)**	**0.88 (1.21)**	**0 (0.00)**	**1.08 (1.48)**	**0 (0.00)**
	-0.000 (0.001)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Log population	**0 (0.00)**	**0 (0.00)**	**1.20 (1.68)**	**0 (0.00)**	**9.50 (9.96)**	**0 (0.00)**
	0.000 (0.000)	0.000 (0.000)	-0.001 (0.010)	0.000 (0.000)	0.008 (0.029)	0.000 (0.000)
Mean rearrest time	**98.54 (1.58)**	**100 (0.00)**	**0.90 (1.37)**	**0.94 (1.30)**	**100 (0.00)**	**46.62 (32.34)**
	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.001 (0.000)	-0.000 (0.000)
% Recidivists	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**	**100 (0.00)**
	0.030 (0.002)	0.030 (0.002)	0.031 (0.006)	0.035 (0.003)	0.027 (0.004)	0.035 (0.007)

Table A.1: Posterior probabilities and their standard deviations, and posterior parameter estimates and standard deviations