Predicting New Criminal Convictions while on Parole: The Role of Offense Type

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Abstract

Understanding factors behind sustained criminal justice involvement is a primary focus of criminal justice research and professionals. Here we examine the relationship between offense type and new criminal convictions for offenders on parole in Utah. By analyzing 3,173 parolees released from Utah's state prison in 2013 and 2016, we find that offenders convicted of a sex-offense have a reduced likelihood of being convicted of a new crime when compared to other offense types using an average follow-up time of 382.5 days. We further find that new criminal convictions while on parole are predominantly made up of non-violent offenses, with less than 2 percent of sex-offenders being re-convicted of a sex-related crime. The costs associated with incarceration and lengthy supervision terms merits a careful evaluation of the risk, severity, and cost of a particular offense to re-occur.

Keywords: risk to re-offend, survival analysis, Bayesian methods

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1 Introduction

Understanding and properly treating factors that lead to sustained criminal justice involvement is a primary goal of criminal justice research and professionals. To aid in this process, risk[1] and needs screenings and assessments are becoming increasingly used at different stages in the criminal justice system. These instruments, which are available for the general offender population and for specific target populations have shown to have a high degree of accuracy in predicting the likelihood of re-offense as offenders are supervised in the community.[2] While risk and needs assessments provide the most accurate information in evaluating an offenders risk to re-offend, both the *risk* and *severity* of a particular crime to be repeated are important policy considerations. As an aid, literature on the taxpayer and victim costs associated with different crime categories may help guide these policy decisions. Indeed, estimating the cost of crime to society has been of interest to researchers, policy makers, and criminal justice professionals for many decades. These costs are typically calculated by examining the unit cost associated with a particular crime type and the probability that such crime will be repeated. These studies typically separate expenditures into direct, indirect, and intangible costs of crime.[3] Furthermore, policy makers may make use of societal values and expectations concerning specific sentence severity and resource allocation.

Historically, and similar to other states, the majority of Utah's prison returns have been attributed to one or more technical violations. The rate of these technical returns may fluctuate through time and is in part, driven by enforcement policies and practices. Because technical violations tend to be different than a new criminal conviction, scholars concerned with *desistance theory*[4] have in recent years called for a distinction between the two. Additionally, examining additional layers of sustained criminal justice involvement, including the severity and type of new offenses as well as time to failure while under community supervision has been encouraged.

To address these concerns, this study applies survival analysis to model time-to-

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[1]Risk is referred to the probability or likelihood of re-offense.

[2]See e.g., Lowencamp et al. (2009)

[3]See Wickramasekera et al. (2015) for a systematic review of the cost of crime. As noted by the Wickramasekera and colleagues, costs of crime estimates are fairly outdated and in-need of unified standards. Further see Fowles and Nystrom, (2012) for Utah specific cost estimates.

[4]See Kazemian 2015 for a definition and review of desistance theory.

event data, where an event is a return to prison caused by one or more new criminal convictions. Specifically here we focus on the relationship between offense type and new criminal convictions for offenders on parole in Utah. We further examine the severity of these new criminal convictions, focusing specifically on violent and sex-related offenses. The following section provides a discussion around the data and statistical methodology. Section three presents the regression results and notes the study limitations. Lastly, section four concludes while providing sound policy considerations.

2 Data & Method

2.1 Data

As informed by the literature,[5] demographics, including age at parole start, gender, and race/ethnicity are included as important control variables. Additionally, explanatory variables, including the parolee's offense severity (felony 1, felony 2, or felony 3), an indicator variable denoting if the current parole start is the first start associated with the current incarceration, and risk to re-offend score are included in the model.[6] The outcome variable of interest "nc_2" denotes a return to prison within 2-years of parole start while "parole_los" denotes the number of days spent on parole before being revoked to prison or discharged. A full definition of variables is presented in Table 1.

[5]For a review of established predictor of recidivism see for example, Stahler et al. (2013).

[6]The parolee's risk to re-offend categorical score is evaluated by the Level of Service: Risk-Need-Responsivity [LS:RNR] instrument. This variable was transformed into a binary variable indicating high/intensive risk versus low/moderate risk.

Table 1: Definition of variables

Variable name	Description
nc_2	Indicates if the parolee was revoked to prison on a new conviction within 2 years
parole_los	Number of days on parole
age	Age (in years) at parole start date
male	Indicates if the offender is male
minority	Indicates if the offender is of minority status
severity	Categorical variable indicating the severity of the current offense (Felony 3, Felony 2, or Felony 1, with Felony 1 being the most severe)
first_parole	Indicates if this is the first parole start associated with the current conviction
high_risk	Indicates if the parolee is high/intensive risk to re-offend
dp_only	Indicates if the primary offense was a drug possession only offense
alch_drug	Indicates if the primary offense was a alchohol and drug related offense
driving	Indicates if the primary offense was a driving offense
person	Indicates if the primary offense was a person offense
property	Indicates if the primary offense was a property offense
weapons	Indicates if the primary offense was a weapon offense
murder	Indicates if the primary offense was a murder offense
sex_offense	Indicates if the primary offense was a sex offense
other	Indicates if the primary offense was categorized as "other"

A total of 3,173 unique parole starts were obtained from the Utah Department of Corrections' (UDOC) database O-Track and then followed for a maximum of two years.[7] Summary statistics are presented in Table 2. The average length of stay on parole before a revocation or being discharged was 382.5 days, or 1.05 years. Overall, 84 percent of the parolees were males and had an average age of 35. Seventy-one percent were high or intensive risk to re-offend, which differed by group (see figure A.1 in Appendix A). Specifically, the percent of parolees that were high or intensive risk to reoffend had a range between 44 (those whose primary offense was a sex offense) and 82 percent (those whose primary offense was a drug possession only offense).

In terms of the parolee's primary offense type,[8] property offenses (32%) made up the largest percent of offenses followed by person offenses (19%), sex offenses (15%),[9] alcohol/drug and drug (13%), and drug possession only offenses (9%). A smaller percent of offenders pertained to driving, weapon, murder,[10] and a category denoted as "other" offenses. Summary statistics (mean values) by offense type are further available in Table A.1 in Appendix A.

[7] The sample consists of 6-months cohorts (yearly October-March unique parole starts). Each observation is defined as a unique combination of a parole start date and an O-Track identifying number. The first parolee started parole in October of 2013 while the last parolee started parole in March of 2016. A small number of observations were originally removed as either they died while on parole or complete information regarding their records was missing (< 2 percent of the sample).

[8] The parolee's primary offense is the most severe offense associated with his/hers incarceration period (prior to the current parole start).

[9] The variable denoting a sex offense includes both registerable and non-registerable sex offenses.

[10] It should be emphasized that only a small percent of offenders convicted of murder will be paroled in the state of Utah. The observations included in this study are hence not representative of all offenders convicted of such an offense.

Table 2: Summary statistics (N=3,173)

Variable	Mean	Sd	Min	Max
nc_2	0.13	0.34	0.00	1.00
parole_los	382.53	257.11	0.00	730.00
age	35.42	9.68	17.27	81.49
male	0.84	0.37	0.00	1.00
minority	0.31	0.46	0.00	1.00
high_risk	0.71	0.45	0.00	1.00
first_parole	0.29	0.45	0.00	1.00
severity*	1.54	0.67	1.00	3.00
dp_only	0.09	0.28	0.00	1.00
alch_drug	0.13	0.34	0.00	1.00
person	0.19	0.39	0.00	1.00
property	0.32	0.47	0.00	1.00
driving	0.07	0.26	0.00	1.00
sex	0.15	0.35	0.00	1.00
weapons	0.02	0.14	0.00	1.00
murder	0.01	0.12	0.00	1.00
other	0.02	0.14	0.00	1.00

2.2 Method

Here we use Bayesian Model Averaging (BMA) to identify the variables that are important in predicting a new criminal conviction while on parole.[11] BMA was selected for the study because of its ability to identify the most relevant variables out of a set of candidates when the assumptions of more conventional techniques are likely unmet. For instance, conventional methods generally require that the true model is known and that all of the relevant variables from the model have been included in the analysis. These assumptions are rarely met in the real world and are likely unmet by the conditions of this study. In addition, a substantial degree of correlation exists among some of the variables included in this study. Results of traditional methods are unreliable under such circumstances; BMA, on the other hand, has shown to be reliable even in the presence of high degree of collinearity.

[11] Please see Hoeting et al. (1999) and Hernández et al. (2018) for a comprehensive overview of BMA.

BMA can be used in a wide range of applications, including for underlying linear, generalized linear, survival, and tree ensemble model classes. This study employed an underlying survival model class to account for the censored properties of the current data structure.[12] The most commonly used survival model is the Cox Proportional Hazard model. Under this approach, the effect that a particular covariate has on the rate that some event will occur is examined. For ease of interpretation, the regression coefficients can be expressed as Hazard Ratios by taking their anti-log. The Hazard Ratio is defined as the risk of experiencing an outcome at time t, given that the individual has already avoided the outcome at a specific point in time. Interpretation of Hazard Ratios is fairly straightforward in that a Hazard Ratio (1) equal to one denotes no difference between groups, (2) below one indicates an improved survival probability, and (3) above one suggests a reduced survival probability.[13]

3 Discussion

3.1 Survival Analysis

BMA was carried out using the bic.surv function in R's BMA package. Figure 1 illustrates the individual effect sizes and their associated error bands obtained from the BMA regression output. A red color denotes a positive relationship with the dependent variable and a green color denotes a negative relationship. A grey color indicates no relationship between the dependent variable and a particular explanatory variable.

In examining the specific regression coefficients, the coefficient for male is 0.52, which yields a hazard ratio of 1.69. Being male is hence associated with a reduced survival probability of 69 percent. Similarly, high/intensive risk parolees have a reduced survival probability of 77 percent in comparison to low/moderate risk offenders. The coefficient for the variable first_parole is -0.52, and a corresponding hazard ratio of 0.59. Parolees on their first parole start is hence associated with an increased survival probability of 41 percent in comparison to those that have had at least one prior parole start.

[12] Fifty percent of the sample was returned to prison on one or more technical violations within the 2-year follow-up time, with a small percent being directed to a parole violator center.

[13] For a mathematical overview of the Cox Proportional Hazard model, please see, Cox (1978).

Person offenses were excluded from the analysis thereby serving as a reference to the other offense types. Similarly, Felony 3 offenses serve as a reference to Felony 2 (severity2) and Felony 1 (severity3) offenses. The only primary offense type important in predicting changes to the hazard rate is the variable indicating a sex offense. Specifically, this variable has a coefficient of -1.17, yielding a hazard ratio of 0.31. Parolees whose primary offense was a sex offense is hence linked to an increased survival probability of 69 percent. The full BMA regression output is available in Appendix B (table B.1).[14]

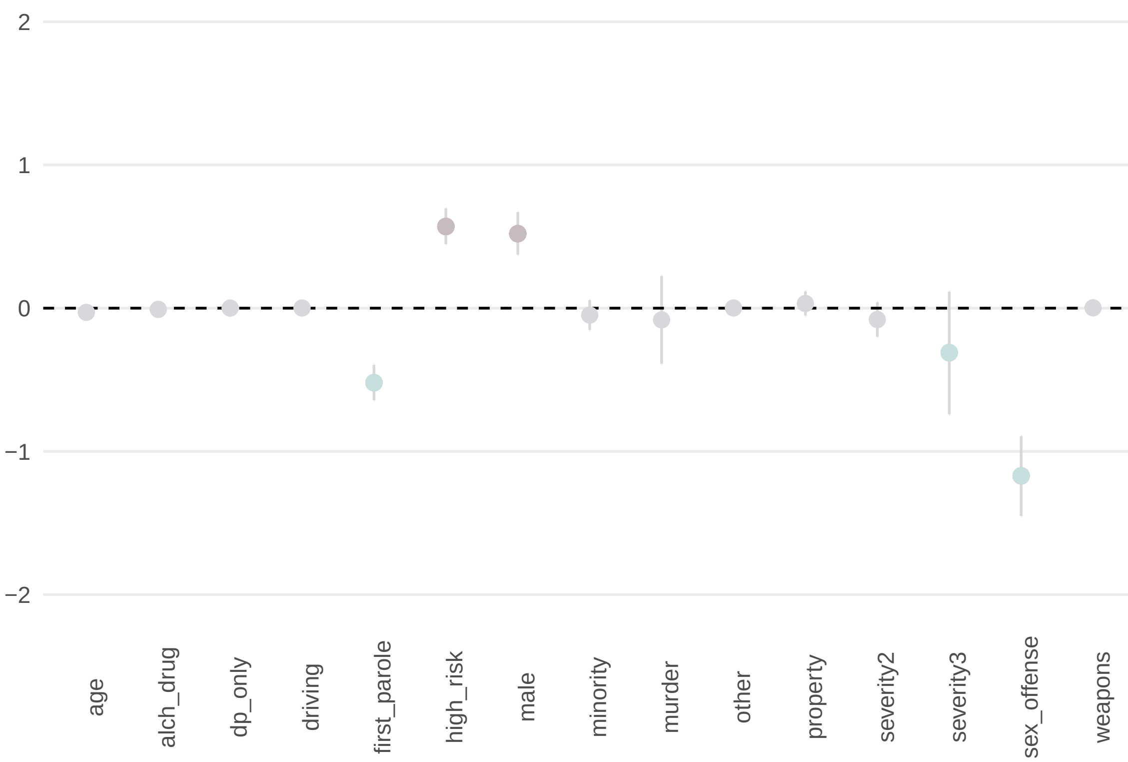

Figure 1: Expected values with error-bands

[14]A secondary analysis was conducted using the sex_offense variable as a standalone binary variable. The result of the analysis as it pertains to variable importance and coefficient size was similar to the above analysis.

3.2 Severity of New Convictions

3.2.1 All New Convictions

In this section we explore the severity of the new criminal convictions that occurred during the two-year follow-up time. Specifically, here we examine the nature of these offenses.[15] Figure 2 illustrates the distribution of offenses that constituted these new criminal convictions. As seen in the figure, close to 30 percent of new convictions while on parole were drug possession only offenses. This was followed by person offenses (24%), other (13%), driving (12%), person (9%), alcohol/drug (8%), weapons (4%), and sex offenses (1%).

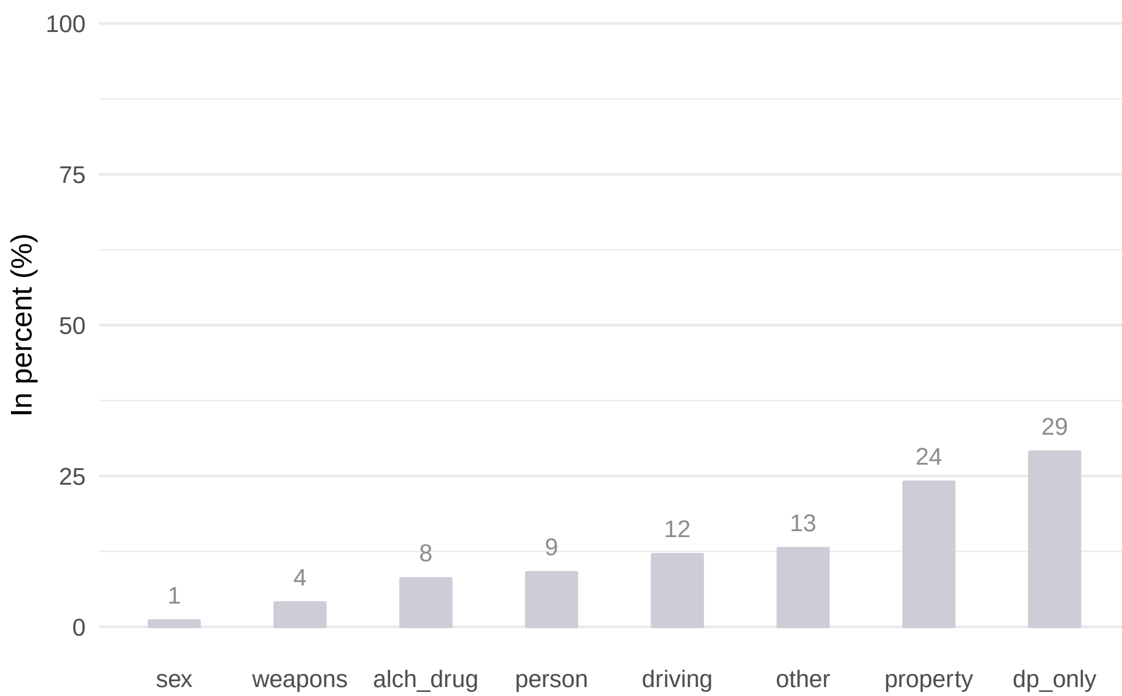

Figure 2: Distribution of all new criminal convictions while on parole

[15]This section examines the entire sample, including the small number of offenders excluded in the BMA analysis who did not have a risk-to-reoffend score. Furthermore, to understand the volume of new convictions that occurred and its distribution, here we do not examine the highest offense severity, but rather, analyze all new convictions.

3.2.2 New Convictions: Sex Offenders

This next section analyzes new criminal convictions while on parole specific to those originally convicted of a sex offense.[16] Table 3 shows the number and rate of new convictions that pertained to the parolees incarcerated for a sex-offense (n=472).[17] A total of 19 (4%) of these offenders had a new conviction within the two-year follow-up time.[18] Two of these convictions pertained to a new sex-offense and five additional unique cases pertained to a violation of or around sex-offender registration.[19]

In placing these rates in context to existing literature, it should be emphasized that differences in data, populations, sample size, methodology, and outcome measures have resulted in a large range of recidivism estimates among convicted sex-offenders (as cited by Bench & Allen, 2013). When recidivism is defined as a new sex related crime, a robust body of research is rather uniform in their findings. Specifically, a large number of studies published in the past two decades have found a sex-related re-offense rate between 5 and 12 percent using a follow-up time between 5 and 16 years (see e.g., Bench & Allen, 2013; Zgoba & Simon, 2005; Sample & Bray, 2003; Hood, Shute, Feilzer & Wilcox, 2002). While Utah specific studies are rare, Bench and Allen (2013) conducted a longitudinal study following 389 sex offenders in Utah for an average of 16 years. By using logistic regression techniques, the researchers found a sex related re-conviction rate of 10 percent. Indeed, similar to Utah's general offender population, the majority of these offender were returned to prison for technical violations.

[16] It should again be noted that the parolee's primary offense denotes the most severe offense. Put differently, a parolee may have had a sex offense conviction but be categorized as a non-sex offender if other convictions were considered more severe.

[17] Since this section is soley analyzing descriptive statistics, here we include all offenders originally convicted of a sex crime, including the eight individuals that were excluded from the survival analysis seen in section 3.1.

[18] It should be emphasized that a large percent of parolees were revoked to prison on one or more technical violation during the 2-year follow-up time, thereby reducing their available follow-up time to less than 2 years. Specifically, while imposing a 2-year cutoff time, the average number of days on parole among this group was 528.7, or 1.45 years.

[19] It may be noted that the low sex specific re-conviction rate prevents a statistical comparison of these rates across different offense types.

Table 3: Summary of sex-offenders convicted of a new crime

Offense Type	Number (n)	% all nc
New sex crime	**2**	**0.42**
Sex registration violation	**5**	**1.06**
Other offenses*	**12**	**2.54**
No new conviction	453	95.97
Total	472	100.00

*Here other offenses denotes a non-sex related conviction.

3.3 Study Limitations

Similar to all quasi-experimental designs, the lack of random assignment precludes this study from eliminating other factors that may explain differences in outcomes between groups. Furthermore, while a large sample of parolees was included in the study, the low re-conviction rate may affect variable inclusion as determined by the BMA averaging process. Additionally, this limits the ability to statistically compare possible differences in the type of convictions that occurred while on parole among different groups of offenders.

The relationship between technical violations and new criminal convictions should be stressed as well. Indeed, revocations caused by technical violations hinder our ability to understand the rate of new criminal convictions that might occur in their absent.[20] Lastly, while it is well established that the majority of offenders who fail on supervision due so within the first 6-months to one year of release, future research may explore these re-conviction rates using a longer follow-up time.

4 Conclusion & Policy Considerations

This study examined the relationship between offense type and new criminal convictions on time-to-event data. By analyzing over 3,000 parolees released from

[20]As previously mentioned, 50 percent of the sample was revoked on one or more technical violations within the 2-year follow-up time, with a small percent being directed to a parole violator center. This number was reduced to 37 percent amongst those whose primary offense was a sex offense.

Utah's state prison in 2013 and 2016, we find that offenders whose primary offense was a sex-offense have a reduced likelihood of being convicted of new crime using an average follow-up time of 382.5 days. Direction of findings are similar to the national literature and further showed that new convictions amongst all offenders while on parole are predominantly made-up of non-violent offenses. Findings specific to convicted sex-offenders demonstrated an overall 4 percent re-conviction rate, with less than 2 percent of these convictions being related to a new sex crime *or* a violation of or around registering as a sex offender.

Policy makers should compare the likelihood and severity of a particular offense to re-occur when finding the appropriate balance between sentence type and length while taking into consideration society's values and expectations as they relate to justice, public safety, and resource allocation. Updating and refining current Utah specific cost estimates may aid in this process.

APPENDICES

Appendix A - Descriptive Statistics

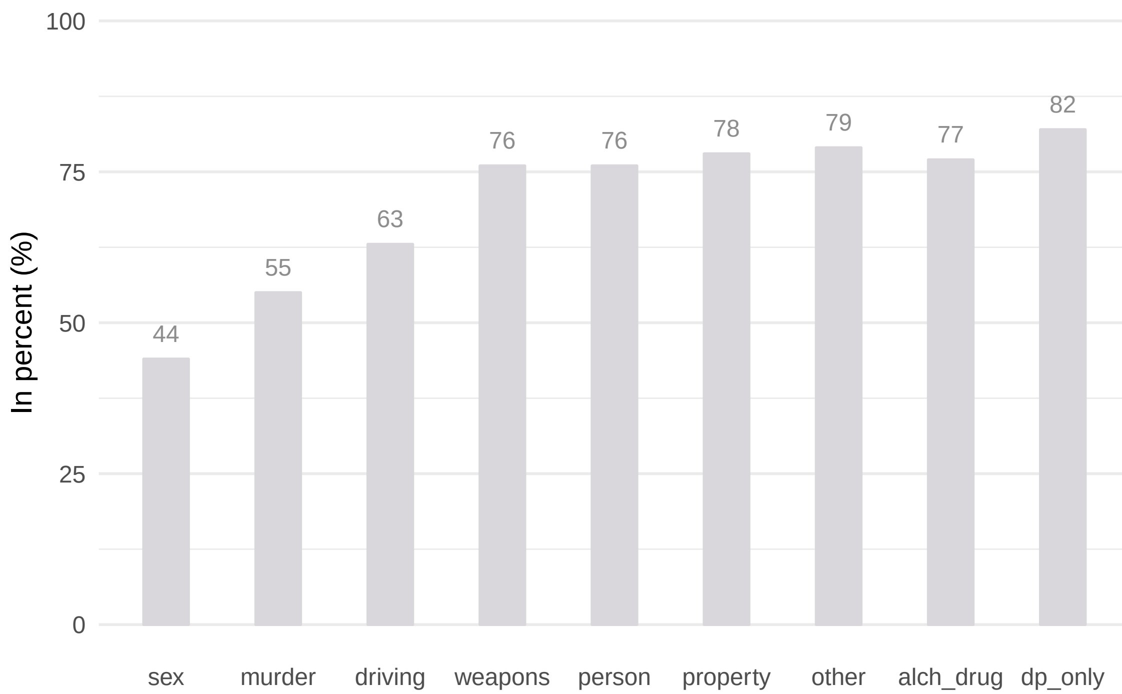

Figure A.1: Percent high/intensive risk to re-offend by primary offense type

Table A.1: Summary statistics by primary offense type (mean values)

Variable	dp_only (n=272)	alch_drug (414)	person (n=602)	property (n=1,011)	driving (n=234)	sex (n=464)	weapons (n=62)	murder (n=47)	other (n=67)
nc_1	0.09	0.07	0.10	0.13	0.10	0.03	0.15	0.04	0.12
nc_2	0.14	0.13	0.14	0.16	0.15	0.04	0.16	0.06	0.13
age	34.37	34.42	33.48	33.37	39.66	41.38	33.90	37.91	37.54
male	0.66	0.79	0.89	0.80	0.89	0.97	0.94	0.89	0.87
minority	0.24	0.36	0.42	0.23	0.33	0.28	0.56	0.36	0.25
married	0.14	0.17	0.14	0.14	0.13	0.21	0.16	0.19	0.18
high_risk	0.82	0.77	0.76	0.78	0.63	0.44	0.76	0.55	0.79
first_parole	0.23	0.27	0.29	0.23	0.30	0.43	0.32	0.51	0.33
severity*	1.26	1.67	1.67	1.26	1.07	2.31	1.26	2.32	1.10

Appendix B - Regression Output

Table B.1: Bayesian model averaging

18 models were selected. Best 5 models (cumulative posterior probability = 0.73)

	p! = 0	**EV**	**SD**	**m1**	**m2**	**m3**	**m4**	**m5**
age	100.0	-0.03	0.01	-0.03	-0.03	-0.03	-0.03	-0.03
male	100.0	0.52	0.15	0.54	0.51	0.52	0.51	0.55
minority	22.0	-0.05	0.10			-0.23		-0.21
high_risk	100.0	0.57	0.12	0.56	0.57	0.59	0.57	0.58
first_parole	100.0	-0.52	0.12	-0.51	-0.54	-0.52	-0.52	-0.50
severity	39.1							
		-0.08	0.12	-0.21				-0.20
		-0.31	0.43	-0.81				-0.79
dp_only	1.2	0.00	0.02					
alch_drug	4.8	-0.01	0.05					
driving	1.3	0.00	0.02					
property	16.7	0.03	0.08				0.21	
sex_offense	100.0	-1.17	0.28	-1.01	-1.29	-1.29	-1.21	-1.02
weapons	2.4	0.00	0.05					
murder	10.4	-0.08	0.31					
other	1.2	0.00	0.04					
nVar				6.00	5.00	6.00	6.00	7.00
BIC				-147.57	-147.54	-145.99	-145.71	-145.18
post prob				0.23	0.23	0.10	0.09	0.07

p!=0 denotes the posterior inclusion probability, defined as the percent of time a variable is part of the models selected by BMA. When this value is 100, it implies that the variable was part of 100 percent of the models. Similarly, a value of 0 denotes that the variable was excluded from the BMA averaging process.

EV denotes the expected value comprised of the coefficients weighted by their posterior probability.

SD is the standard deviation.

nVar denotes the number of variables included in each of model selected by BMA.

BIC denotes the Bayesian Information Criterion. The model with the lowest BIC score is preferred.

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