Examining Parole Revocation Patterns

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Executive Summary

In the state of Utah, a revocation to prison from parole can occur in two instances, (1) if the offender failed to comply with their supervision conditions and (2) if the offender was convicted of a new crime while on parole. It should be emphasized that changes in revocation rates through time may not speak to changes in offender behavior but rather the nature and enforcement of criminal justice policies and practices. Additionally, it may not be reflective of general health trends and other dynamic social phenomena. With this in mind, this study examines revocation patterns through the lens of Utah's current criminal justice policies using a one-year follow-up time.[1] Its main findings may be summarized as follows:

- **While ceilings on parole revocations are reducing parole violators' prison length of stay**, previous parole violators are continuing to cycle through the system. Such findings hint at an increased need of effective interventions for this on average, high risk population.

- **Increases in new convictions while on parole are being driven by *non-violent* offenses.** Such non-violent offenses are primarily comprised of drug possession only crimes.

The above findings warrant a closer look at the *causes* behind revocations, their interplay with revocation length of stay, implementation fidelity, organizational capacity, and current enforcement practices. Overall, nuances of these findings highlight the continuing need to collect and monitor data as well as the importance of conducting further analyses to elucidate current criminal justice trends.

[1] Here we do not speak to a specific current criminal justice policy, but rather examine general recidivism patterns as Utah implements broad criminal justice reform.

1. Introduction & Background

Due to in part, a faster than average growing population, Utah's prison population increased by nearly 20 percent between 2004 and 2013. This coupled with a stubbornly high recidivism rate inspired the creation of broad criminal justice reform. The main objectives of the reform were to stop the revolving prison-door, hold offenders accountable, and increase public safety while saving tax dollars spent on crime.[2] To meet such objectives, a wide array of evidence informed policies was implemented in October 2015, affecting all stages of the criminal justice system.

One of these policies included placing graduated ceilings on the length of time a parolee could serve in prison after being revoked from parole.[3] In the state of Utah, a revocation or return to prison from parole can occur in two distinct cases, (1) if the offender failed to comply with their supervision conditions, and (2) if the offender was convicted of a new crime while on parole. Following the implementation of the reform, preliminary analyses showed that offenders post-reform were spending less time in prison upon a revocation from parole.[4] While such a finding aligns with the intent of current criminal justice policies, an area that remains unexplored pertains to the rates of revocations from parole while controlling for changes in the parole population that may be occurring through time.

This current study explores parole revocation patterns as they relate to Utah's criminal justice reform. It should be emphasized that it does not speak to a specific policy, but rather examines general trends in revocations as reform efforts are being implemented. It proceeds as follow. Section two provides a detailed discussion around the data and methodology while section three interprets the results from the regression analysis. The fourth section concludes by noting the study limitations and providing a direction for further research.

[2] See the 2014 Justice reinvestment report for an in-depth overview of these policies.
[3] Such a policy was implemented as research indicate that reducing average prison length of stay can lead to substantial long-term cost savings with small impacts on recidivism (see e.g., Rhodes et al. 2018).
[4] See the 2017 Justice reinvestment annual report regarding details about this finding.

2. Data & Methodology

2.1 Data

A total of 4,541 unique parole starts were obtained from the Utah Department of Corrections' (UDOC) database O-Track.[5] In order to delineate the pre and post-reform time frames, these data were divided into four distinct cohorts. The first cohort had a parole start date between October 1, 2013 and March 31, 2014; the second cohort[6] started parole between October 1, 2014 and March 31, 2015; the third cohort had a parole start date between October 1, 2015 and March 31, 2016; the fourth cohort started parole between October 1, 2016 and March 31, 2017. Each cohort was followed for one year from their respective parole start date. The outcome variables of interest were separated into two binary variables where the first denotes whether the parole was returned on a technical violation only and the second denotes a revocation based on a new conviction.

To account for changes in the parole population and as informed by prior literature, demographics in the form of age and gender serve as important covariates.[7] Additionally, criminal justice variables comprising of offense type, offense severity, and the parolee's risk to reoffend (available through the Level of Service: Risk-Need-Responsivity [LS:RNR] instrument) are included.[8] Lastly, a binary variable indicating if the current parole start was the first start associated with the current conviction(s) is included in the model.

A categorical variable indicating the four distinct time periods described above is the main predictor variable of interest. Cohort one (October 1, 2013 and March 31, 2014), and cohort two (October 1, 2014 and March 31, 2015), represents the two pre-reform periods. Cohort three (October 1, 2015 and March 31, 2016), and cohort four (October 1, 2016 and March 31, 2017), denotes the two post-reform periods respectively. Cohort one is excluded from the analysis and hence serves as a reference to cohorts two, three, and four. These variables are further described in Table 1.

[5] A unique parole start is defined as a combination of a unique identification number (Otrack number) and parole start date. 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).
[6] It should be noted that the follow up time for cohort two entails the possibility of impact by criminal justice reforms. This implies that individuals who returned to prison between October 2015 and March 2016 cannot be entirely categorized as pre-reform.
[7] For a review of established predictor of recidivism see for example, Stahler et al. (2013).
[8] The LS:RNR is a validated risk assessment instrument that categorizes offenders as low, moderate, high and intensive risk to reoffend. UDOC implemented this version of the Level of Service in 2015. Due to concerns about the comparability of different risk assessment versions through time, the variable was grouped into low/moderate versus high/intensive risk to reoffend.

Table 1. Definition of variables

Variable name	Description
revocation_tech	Indicates if the parolee was revoked to prison on a technical violation only
revocation_nc	Indicates if the parolee was revoked to prison on a new conviction
age	Age (in years) at parole start date
male	Indicates if the offender is male
minority	Indicates if the offender is of minority status
married	Indicates if the offender is married
violent_offense	Indicates if the current offense was a violent crime
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
cohort	Categorical variable denoting the different cohorts (1-4)

Summary statistics by cohort is presented in Table 2. The mean one-year return to prison rate due to a technical violation was 35 and 38 percent for cohorts one and two while the mean rate was 46 for cohort three.[9] The mean one-year return to prison rate due to a new conviction was 10 percent for cohorts one and two, 9 percent for cohort three and 14 percent for cohort four.

Observed differences in the mean covariate values can be seen across groups. Specifically, the percent of offenders who are high/intensive risk to reoffend is highest among cohort four parolees at 77 percent. Furthermore, in comparison to cohort one, later cohorts had a higher percentage of offenders whose current offense was violent. In all cohorts, males made up the larger percent of parolees with a range of 82 to 87 percent. Lastly, the percent of parolees whose current parole start was the first start associated with the current offense decreases through time (from 31 to 22 percent). This implies that later cohorts are comprised of more parolees who have failed at least once on a prior parole start.

[9] Due to data quality, this study was unable to evaluate revocations rates due to a technical violation amongst cohort 4 parolees.

Table 2. Summary statistics by cohort (mean values)

Variable	cohort 1 (n=988)	cohort 2 (n=1,073)	cohort 3 (n=1,112)	cohort 4 (n=1,368)
recid_tech	0.35	0.38	0.46	*
recid_nc	0.1	0.1	0.09	0.14
age	34.8	35.5	35.9	36.6
male	0.82	0.83	0.87	0.87
minority	0.3	0.31	0.31	0.32
married	0.15	0.15	0.17	0.14
high_risk	0.71	0.7	0.73	0.77
severity	1.47	1.56	1.59	1.54
violent_offense	0.33	0.37	0.4	0.36
first_parole	0.31	0.29	0.27	0.22

* Due to data quality, this study was unable to evaluate revocations rates due to a technical violation amongst cohort 4 parolees.

2.2 Methodology

Statistical analyses involve uncertainty. Here we apply Bayesian Model Averaging (BMA) to predict the probability of being revoked to prison from parole using two distinct outcome variables. In broad strokes, BMA *averages* across the most likely models and hence involve less uncertainty than more traditional approaches which focuses on one single model. Another advantage of BMA concerns its ability to detect variable importance under situations of high collinearity among two or more predictor variables. When two or more variables have a strong relationship, BMA selects the most likely variable, while reducing the importance of the others.[10] The latter feature is useful in the current context as variables in form of offense type and offense severity often share a moderate to strong relationship. To apply BMA to the current data set, this study uses the bic.reg function from the BMA package in R statistical software.[11]

[10] For an in-depth overview of BMA, please see Hoeting, Madigan, Raftery, & Volinsky (1999), and Onorante & Raftery (2016).

[11] In the Bayesian framework, statistical significance is seen through the lens of "importance," hence the word statistical significance is not used in what follows.

3. Discussion of Results

3.1 Technical Violations

This section explores prison revocations due to one or more technical violations. Figure 1 illustrates the expected revocation rate by cohort.[12] As seen in the figure, the two pre-reform cohorts have a similar expected return rate of 36 percent while cohort three shows an increased expected return rate of 45 percent. The variable denoting whether it was the offender's first parole start was one of the most important variables as determined by the BMA process and depicted a relatively large negative average coefficient (seen in Appendix A). Because this part of the parole population is decreasing through time, such finding warrants a closer look at this subset of the population.

Figure 1. Percent expected to be revoked on a technical violation

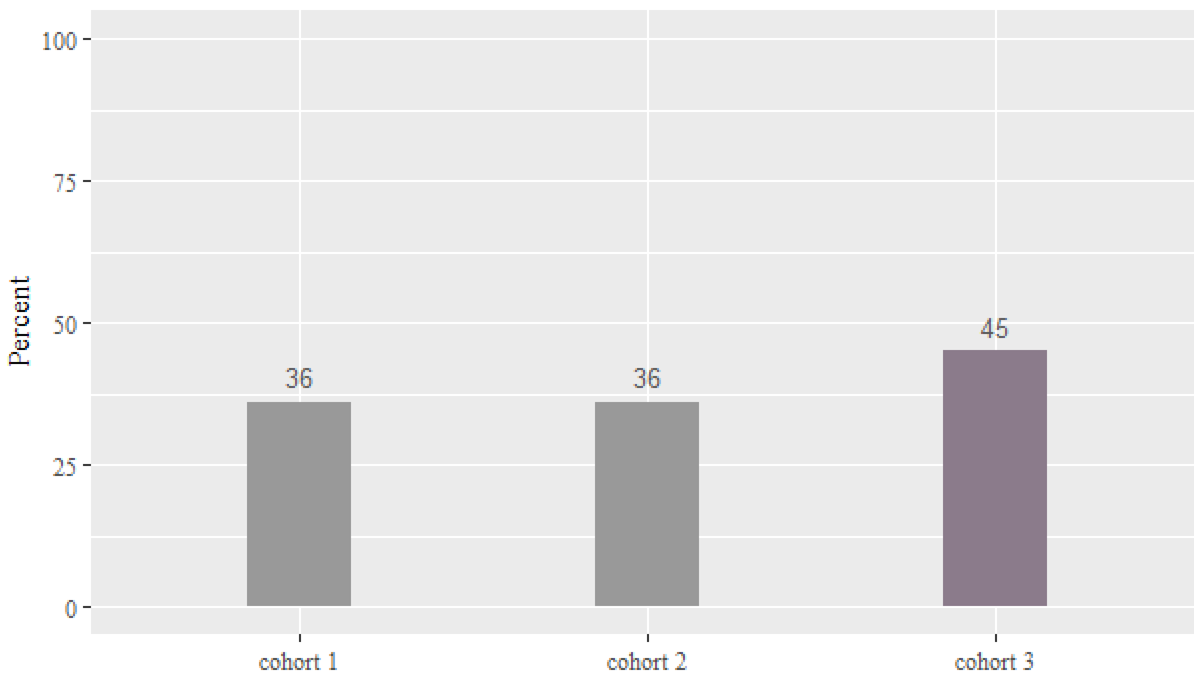
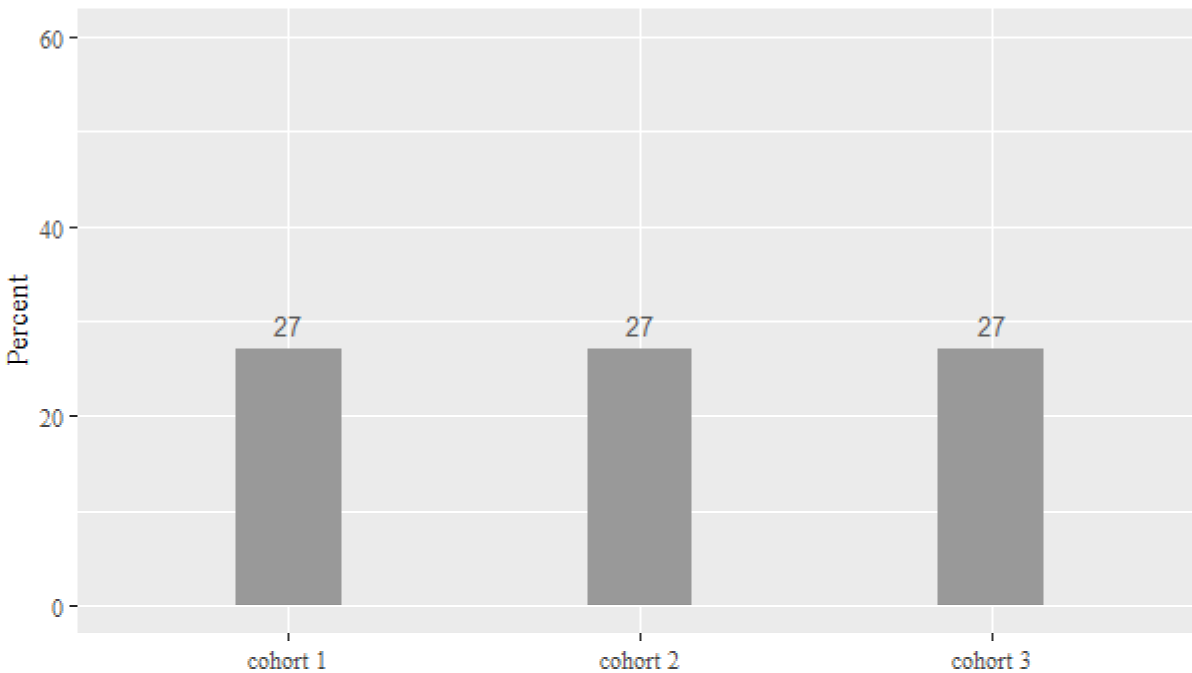


Figure 2 illustrates the expected revocation rates by cohort by restricting the sample to those that are on their first parole start. As seen in the figure, all three cohorts have a similar expected rate at just below 30 percent. Hence the BMA process is not highlighting a difference in the

[12] The expected revocation rates were estimated using the coefficients from the BMA process, evaluated at the mean values of each covariate (available in Appendix A).

likelihood of being revoked on a technical violation across groups when restricting the sample to this subset of the population.[13]

Figure 2. Percent expected to be revoked on a technical violation: First parole starts only



3.2 New Convictions

This next section examines prison revocations based on a new conviction. As in the previous analysis, Figure 3 illustrates the expected revocation rate by cohort.[14] As seen in the Figure, cohorts one through three have a similar expected return rate of 10 percent. In contrast, cohort four depicts an increased expected return rate of 14 percent. It should be noted that in contrast to the previous analysis, the variable denoting whether it was the parolee's first start was not deemed important by the BMA averaging process. Such results eliminated the need to examine them separately.

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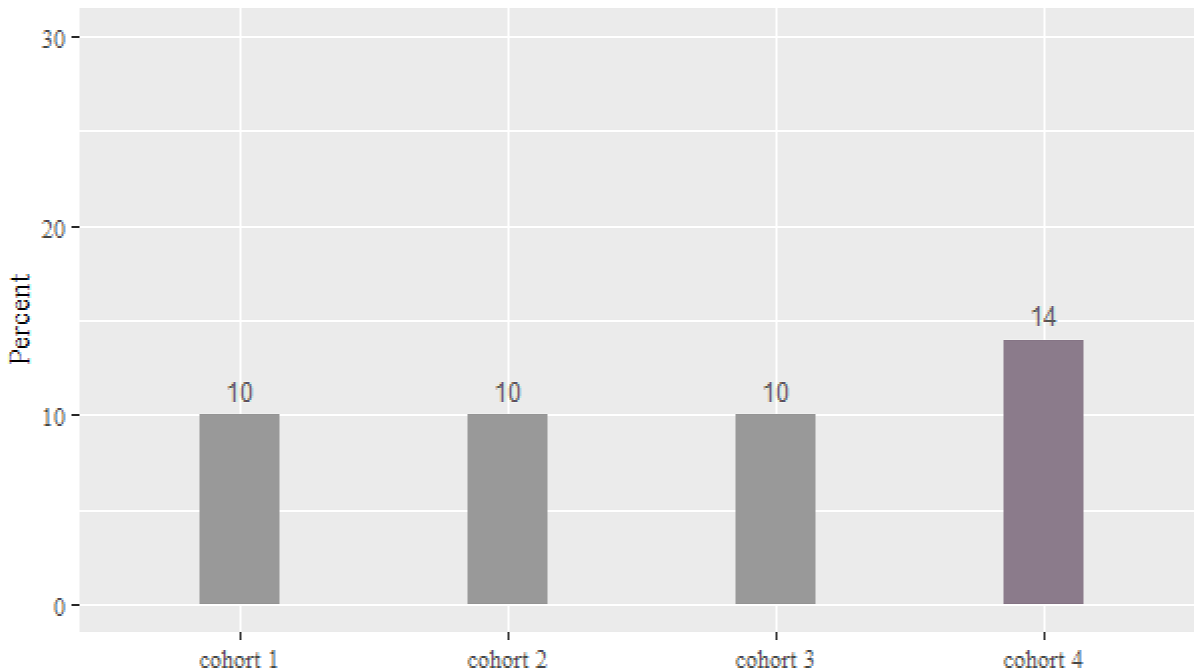
[13] These results were sensitive to the use of statistical method. Future studies may achieve more robust results as sample sizes are allowed to grow.
[14] The expected revocation rates were again estimated using the coefficients from the BMA averaging process, evaluated at the mean values of each covariate (available in Appendix B).

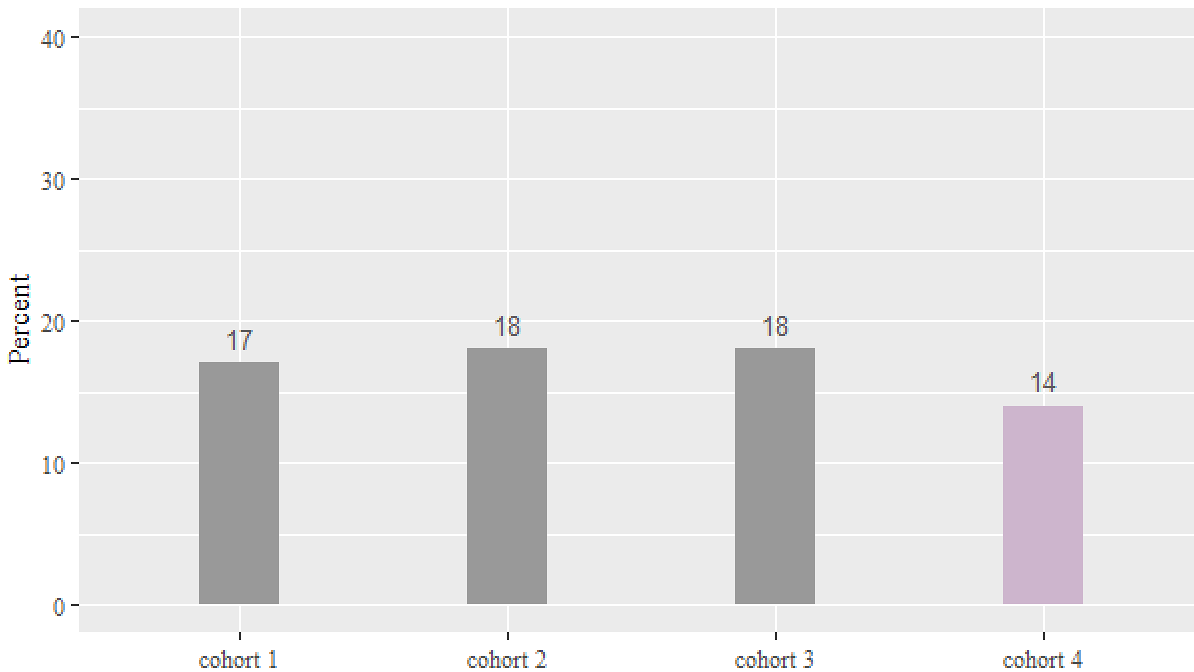
Figure 3. Percent expected to be revoked on a new conviction



Findings from the previous analysis warrant a closer look at the nature of these new convictions. Figure 4 illustrate the percent of these new convictions that were violent by cohort.[15] As seen in the figure, a reduced percent of violent convictions is occurring during the second post-reform time period. More specifically, 17 to 18 percent of offenders among cohorts one and three had a new conviction that pertained to a violent crime. In comparison, 14 percent of offenders in cohort four had a violent conviction. This implies that while new convictions are increasing in the second post-reform cohort, this increase is driven by non-violent convictions. Further descriptive analysis revealed that of these non-violent convictions, cohort four had the highest percent of drug possession only convictions.

[15] A parolee was coded violent if they had at least one conviction that was a murder, person, sex-registrable, or weapon related conviction.

Figure 4. Percent of new convictions that are violent



4. Conclusion

4.1 Limitations and Avenues for Future Research

The limitations of comparing recidivism rates through time are emphasized in this section. An important nuance of the current study is its inability to distinguish changes in enforcement policies and practices from changes in offender behavior. Because a revocation to prison from parole may be a direct result of enhanced or reduced enforcement efforts, both as it relates to violations and new convictions, study findings may not speak to actual changes in behavior among the parole population.

The importance of implementation fidelity should be stressed as well. Per implementation science standards, full implementation particularly with fidelity, takes time and requires adequate resources. Hence the impact or effect of any policy change may not come into complete fruition until such resources are available and the subsequent requirements of each policy recommendation take place. As an example, specific recommendations in Utah's broad reform package included improving and expanding reentry and treatment services. It further emphasized the need to ensure *quality* of treatment by establishing statewide standards and certification processes. In regard to designing and tailoring community treatment services to meet the needs of those who are involved in the criminal justice system and ensuring such services adhere to evidence-based practices, such processes may take longer than two years post-reform to actualize (Morris, Woodling & Grant, 2011).

Indeed, the complexity of examining effectiveness of criminal justice policies is highlighted by the underlying assumption of fidelity of such policies which take time to realize. Future research may explore processes around fidelity through the discipline of implementation science. Furthermore, accounting for changes in general social and public health trends, including the current opioid epidemic may assist forthcoming research in contextualizing and identifying pertinent factors to include in future analyses.

4.2 Summary

This study served as a first step in understanding changes in parole revocation patterns as they relate to Utah's broad criminal justice reform. By using advanced statistical techniques, this study found no difference in the likelihood of being revoked due to a technical violation post reform when examining parolees on their first parole start. However, a difference between groups was seen when including parolees that had been revoked at least once before. When examining new convictions, the results demonstrate no difference between groups in the first post-reform cohort; however, a difference was seen in the second post-reform cohort. A closer look at these convictions revealed that such a difference is driven by increases in *non-violent* convictions post-reform.

Overall, study findings warrant a closer look at the *causes* behind revocations, its interplay with policies regarding revocation length of stay, implementation fidelity, enforcement practices, and short- and long-run impacts on the criminal justice population. Overall, the nuances of the findings from this study highlight the continuing need to collect, analyze, and monitor data as well as the importance of conducting further analyses to elucidate current criminal justice trends.

Appendix A

The below shows the BMA regression output for the analysis pertaining to technical violations, highlighting the five most likely models. An explanation of important terms is provided underneath Table A1.

Table A1. Bayesian model averaging - Technical violations

8 models were selected. Best 5 models are shown.

	p!=0	EV	SD	model 1	model 2	model 3	model 4	model 5
Intercept	100	0.499	0.039	0.494	0.516	0.505	0.514	0.476
age	100	-0.007	0.001	-0.007	-0.007	-0.006	-0.006	-0.007
male	4	0.002	0.009	.	.	.	.	.
minority	0	0	0	.	.	.	.	.
married	3.5	-0.001	0.008	.	.	.	.	.
high_risk	100	0.195	0.019	0.196	0.194	0.191	0.189	0.196
severity2	28.9	-0.014	0.023	.	-0.045	.	-0.055	.
severity3	10	-0.006	0.021	.	.	.	-0.07	.
violent_offense	7.7	-0.003	0.011	.	.	-0.037	.	.
first_parole	100	-0.12	0.019	-0.121	-0.12	-0.118	-0.117	-0.12
cohort2	4.1	0.001	0.008	.	.	.	.	0.036
cohort3	100	0.091	0.018	0.089	0.092	0.091	0.093	0.108
nVar				4	5	5	6	5
r2				0.089	0.091	0.091	0.093	0.09
BIC				-264.7	-263.2	-261.1	-260.7	-259.8
post prob				0.483	0.224	0.077	0.065	0.041

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.
r2 is each model's r-squared.

Table A2. Bayesian model averaging - Technical violations
First parole starts only

19 Models were selected. Best 5 models are shown.

	p!=0	EV	SD	model 1	model 2	model 3	model 4	model 5
Intercept	100	0.236	0.089	0.206	0.344	0.158	0.22	0.336
age	39	-0.001	0.002	.	-0.003	.	.	-0.004
male	9.5	0.008	0.028	.	.	.	.	.
minority	0	0	0	.	.	.	.	.
married	11.3	-0.008	0.026	.	.	.	-0.07	.
high_risk	100	0.199	0.032	0.198	0.187	0.21	0.194	0.185
severity2	67.8	-0.064	0.051	-0.094	-0.098	.	-0.09	-0.1
severity3	83	-0.126	0.072	-0.166	-0.151	-0.122	-0.159	-0.154
violent_offense	6.4	-0.005	0.02	.	.	.	.	.
cohort2	0	0	0	.	.	.	.	.
cohort3	11.3	0.007	0.021	.	.	.	.	0.064
nVar				3	4	2	4	5
r2				0.082	0.088	0.073	0.086	0.092
BIC				-57.3	-56.5	-55.1	-54.3	-54.2
post prob				0.247	0.162	0.08	0.053	0.051

Appendix B

The below shows the BMA regression output for the analysis pertaining to new convictions, highlighting the five most likely models. An explanation of important terms is provided underneath Table B1. The results are further illustrated in Figure B1.

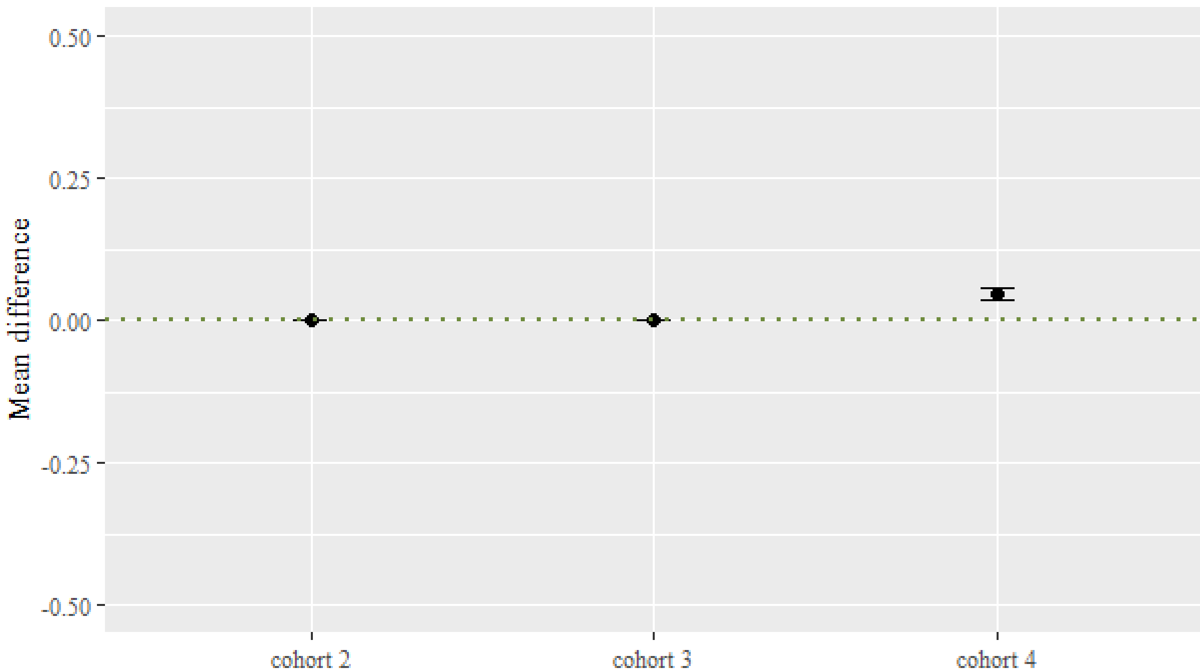
Table B1. Bayesian model averaging - New convictions

21 models were selected. Best 5 models are shown.

	p!=0	EV	SD	model 1	model 2	model 3	model 4	model 5
Intercept	100	0.148	0.03	0.151	0.153	0.123	0.184	0.125
age	96.6	-0.002	0.001	-0.002	-0.002	-0.002	-0.002	-0.002
male	77.5	0.033	0.021	0.043	0.042	0.041	.	0.043
minority	13.8	-0.003	0.009	.	.	.	.	.
married	0	0	0	.	.	.	.	.
high_risk	34.5	0.01	0.015	.	.	0.03	.	0.026
severity2	0	0	0	.	.	.	.	.
severity3	11.1	-0.004	0.014	.	.	.	.	.
violent_offense	100	-0.049	0.01	-0.051	-0.053	-0.05	-0.048	-0.048
first_parole	41.9	-0.013	0.017	-0.031	.	.	.	-0.028
cohort2	0	0	0	.	.	.	.	.
cohort3	0	0	0	.	.	.	.	.
cohort4	100	0.046	0.01	0.045	0.047	0.045	0.048	0.043
nVar				5	4	5	3	6
r2				0.019	0.017	0.019	0.015	0.02
BIC				-45.3	-45.2	-44.5	-43.4	-43
post prob				0.184	0.172	0.124	0.071	0.057

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.
r2 is each model's r-squared.

Figure B1. Mean difference in the probability of being revoked to prison on a new conviction (baseline = cohort 1).



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