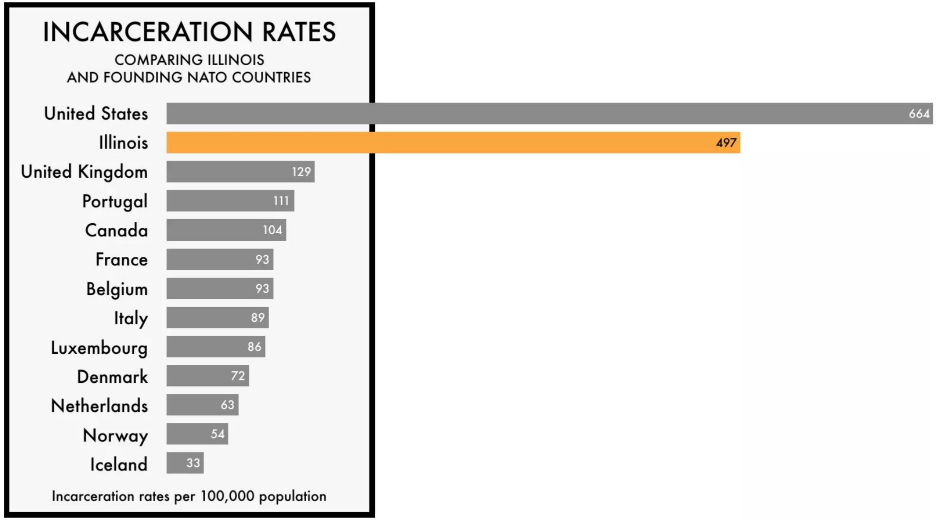
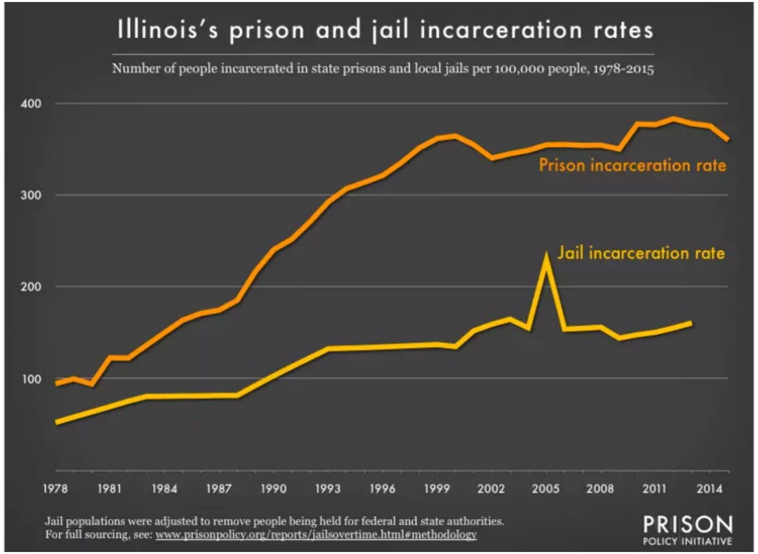
The Impact of COVID-19 on the Sentence Length for Illinois Inmates

Group 6

Background



Source: https://www.prisonpolicy.org/global/2021.html



Today, Illinois's incarceration rates stand out internationally.[1]

Rates of imprisonment at Illinois have grown dramatically in the last 40 years.[1]

The Covid-19 pandemic's impact on criminal justice system

The Covid-19 pandemic has had a profound impact on many aspects of our society, including the criminal justice system. The Covid-19 pandemic has significantly affected the criminal justice system, with many challenges and disruptions, including **difficulty in accessing judicial proceedings for litigants**,[2] **decreased incarcerated population**,[3] and **limitations on in-person visits**.[4]

Difficulty in accessing judicial proceedings for litigants

According to the **Covid-19 and the State Courts Study** conducted by the University of Illinois System's Institute for Government and Public Affairs and the National Center for State Courts, between August 2020 and July 2021, the majority of attorneys reported that **litigants' access to judicial proceedings was more challenging than usual**, particularly regarding building access, transportation, timeliness, location, scheduling, and procedures.[2]

Decreased incarcerated population

During the Covid-19 pandemic from March 1 to October 10, 2020, there was a 19.1% decrease in **California's prison population**, with the number of incarcerated individuals dropping from 119,401 to 96,623.[3]

In **Germany**, to **avoid a potential influx of infected individuals after the Covid-19 pandemic**, the prison population had reduced from 77 to 67 per 100,000 inhabitants by Federal states **refraining from incarcerating short-term prisoners**, such as fine defaulters comprising about 10% of the daily prison population.[4]

Limitations on in-person visits

Personal visits had been restricted due to the pandemic, with **some prisons implementing cut off wheels to separate prisoners from visitors**. While compensatory measures like video calls have been introduced, their effectiveness remains uncertain.[4]

Objective

This study aims to explore the impact of COVID-19 pandemic, along with other variables, including demographics (such as sex, race/ethnicity, and age), veteran status, admission type, and crime class on the **length of sentence years for inmates** who were in custody between January 1st, 2019 to June 30th, 2021.

We hypothesize that the Covid-19 pandemic will have a significant impact on the length of sentence years for inmates, and that this impact will vary depending on demographics and criminal justice-related variables.

Data Description

We utilized the Prison Population Data Sets from the *Illinois Department of Corrections*,[5] which were collected and refreshed annually on March 31st, June 30th, September 30th, and December 31st. The dataset provides a cumulative view of the prisoners in the prison, as it includes information about all individuals who have been incarcerated there up to a certain point in time.[5] In other words, it offers a snapshot of the entire prisoner population at that given time, rather than focusing on a specific subset or sample.

Prison Population Data Sets

- Prison Population on 12-31-22 Data Set
- Prison Population on 09-30-22 Data Set
- Prison Population on 06-30-22 Data Set
- Prison Population on 03-31-22 Data Set
- Prison Population on 12-31-21 Data Set
- Prison Population on 09-30-21 Data Set
- Prison Population on 06-30-21 Data Set
- Prison Population on 03-31-21 Data Set
- Prison Population on 12-31-20 Data Set
- Prison Population on 09-30-20 Data Set

Data Cleaning

- ❖ Collected all incarceration data in Illinois between January 1st, 2019 to December 31st, 2021.
- ❖ Merged the datasets based on column values (original sample size: 395,332).
- ❖ Removed all duplicating inmate records utilizing the uniqueness of inmate ID
- ❖ Dropped all observations containing a NA or “Unknown” or “Other” value.
- ❖ Narrowed down the duration from January 1st, 2019 to June 30th, 2021.
- ❖ Final sample size: 16,976.

Variables of the data

Original Data:
[1] "IDOC #"
[2] "Name"
[3] "Date of Birth"
[4] "Sex"
[5] "Race"
[6] "Veteran Status"
[7] "Current Admission Date"
[8] "Admission Type"
[9] "Parent Institution"
[10] "Projected Mandatory Supervised Release (MSR) Date3"
[11] "Projected Discharge Date3"
[12] "Custody Date"
[13] "Sentence Date"
[14] "Crime Class"
[15] "Holding Offense"
[16] "Sentence Years"
[17] "Sentence Months"
[18] "Truth in Sentencing"
[19] "Sentencing County"

Cleaned Data:
[1] "Sex"
[2] "Race" → [12] "IsWhite"
[3] "Veteran.Status"
[4] "Admission.Type" → [13] "IsReturn"
[5] "Crime.Class"
[6] "Date.of.Birth" → [10] "Age"
[7] "Custody.Date"
[8] "Name"
[9] "Sentence.Years"
[11] "IsPost"

Binary
Sex
IsWhite
Veteran.Status
IsReturn
IsPost

Ordinal
Crime.Class

Numerical
Age (standardized)
Sentence.Years (standardized)

Descriptive Statistics

Compared with PC, AC were:

- Younger
- Sentence years were different
- The proportion of Male and Female is different
- The proportion of White and Other is different
- The proportion of returned/new admission is different
- The proportion for the crime classes were different

Table 1. Summary statistics for the demographics, criminal justice-related variables, and sentence years between the pre-Covid-19 pandemic (PC) and the after-Covid-19 pandemic (AC).

	Total Population	PC	AC	*p*-value
Age	38.19±11.43	38.74±11.60	37.05±11.01	<.001[a]
Male[b]	16,853 (99.275%)	11,321(99.24%)	5,532 (99.35%)	<.001[b]
Female[b]	123 (0.724%)	87 (.763%)	36 (0.647%)	
White[b]	6,936 (40.86%)	4,399 (38.56%)	2,537 (45.56%)	< .001[b]
Other[b]	10,040 (59.14%)	7,009 (61.44%)	3,031(54.44%)	
Veteran[b]	502 (2.957%)	356 (3.120%)	146 (2.622%)	.072[b]
Non-Veteran[b]	16,474 (97.04%)	11,052 (96.88%)	5,422 (97.38%)	
Return Admission[b]	16,203(95.45%)	10994 (96.37%)	5209 (93.55%)	<.001[b]
New Admission[b]	773 (4.55%)	414 (3.629%)	359 (6.45%)	
Class 4[b]	4740 (27.92%)	3366 (29.51%)	1374 (24.68%)	<.001[b]
Class 3[b]	4206 (24.78%)	2734 (23.97%)	1472 (26.44%)	
Class 2[b]	4796 (28.25%)	3029 (26.55%)	1767 (31.73%)	
Class 1[b]	1943 (11.45%)	1313 (11.51%)	630 (11.31%)	
Class X[b]	1232 (7.26%)	919 (8.06%)	313 (5.62%)	
Murder[b]	59 (.0348%)	47 (0.412%)	12 (0.216%)	
Sentence Years	4.15±4.80	4.21±5.06	4.03±4.18	<.001[a]

Abbreviation: PC, pre-Covid pandemic; AC, after-Covid pandemic.
[a] The *p*-value referred to the independent t-test.
[b] All the cells in these rows were referred to as the observation number and the proportion of the total sample. The *p*-value was referred to Pearson's $\chi 2$ (chi-square) statistic.

Frequentist Model

Main Effect:

Sentence Year = $\square_0$ + $\square_1$Age + $\square_2$Sex + $\square_3$IsWhite + $\square_4$Veteran.Status + $\square_5$IsReturn + $\square_6$Crime.Class + $\square_7$IsPost

Interaction:

Sentence Year = $\square_0$ + $\square_1$Age + $\square_2$Sex + $\square_3$IsWhite + $\square_4$Veteran.Status + $\square_5$IsReturn +

$\square_6$IsPost + $\square_7$Crime.Class + $\square_8$Crime.Class:Age + $\square_9$Crime.Class:Sex +

$\square_{10}$Crime.Class:IsWhite + $\square_{11}$Crime.Class:Veteran.Status + $\square_{12}$Crime.Class:IsPost +

$\square_{13}$Crime.Class:IsReturn

Frequentist Model Result

```
Call:
lm(formula = Sentence.Years ~ Age + Sex + IsWhite + Veteran.Status +
    IsReturn + Crime.Class + IsPost, data = train)

Residuals:
    Min      1Q  Median      3Q     Max
-2.1971 -0.3480 -0.0676  0.2101 18.7369

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       -1.116497   0.089160 -12.522  < 2e-16 ***
Age                0.039132   0.007193   5.440 5.42e-08 ***
SexMale            0.051819   0.082094   0.631 0.527911
IsWhite            0.013450   0.014375   0.936 0.349471
Veteran.StatusYes -0.059912   0.042596  -1.407 0.159590
IsReturn          -0.111018   0.033561  -3.308 0.000942 ***
Crime.Class        0.479439   0.005728  83.704  < 2e-16 ***
IsPost            -0.042900   0.014982  -2.863 0.004198 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8132 on 13573 degrees of freedom
Multiple R-squared:  0.3417,    Adjusted R-squared:  0.3414
F-statistic:  1007 on 7 and 13573 DF,  p-value: < 2.2e-16
```

RSS = 2120.3

```
Call:
lm(formula = Sentence.Years ~ Crime.Class * (Age + Sex + IsWhite +
    Veteran.Status + IsPost + IsReturn), data = train)

Residuals:
    Min      1Q  Median      3Q     Max
-2.2781 -0.3533 -0.0704  0.2196 18.7784

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                   -0.548744   0.190327  -2.883 0.003943 **
Crime.Class                    0.179575   0.088329   2.033 0.042070 *
Age                            0.027661   0.015688   1.763 0.077886 .
SexMale                       -0.469540   0.175017  -2.683 0.007309 **
IsWhite                       -0.035454   0.032784  -1.081 0.279507
Veteran.StatusYes              0.043926   0.095223   0.461 0.644596
IsPost                         0.113805   0.034633   3.286 0.001019 **
IsReturn                      -0.194089   0.075670  -2.565 0.010329 *
Crime.Class:Age                0.004837   0.005699   0.849 0.396102
Crime.Class:SexMale            0.279481   0.083709   3.339 0.000844 ***
Crime.Class:IsWhite            0.020461   0.012063   1.696 0.089873 .
Crime.Class:Veteran.StatusYes -0.040709   0.034159  -1.192 0.233388
Crime.Class:IsPost            -0.063369   0.012663  -5.004 5.68e-07 ***
Crime.Class:IsReturn           0.035252   0.028029   1.258 0.208524
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8121 on 13567 degrees of freedom
Multiple R-squared:  0.3438,    Adjusted R-squared:  0.3432
F-statistic: 546.8 on 13 and 13567 DF,  p-value: < 2.2e-16
```

RSS = 2117.4

Bayesian Model (Main Effect)

Main Effect Formula:

Sentence Year = $\square_0$ + $\square_1$Age + $\square_2$Sex + $\square_3$IsWhite + $\square_4$Veteran.Status + $\square_5$IsReturn + $\square_6$Crime.Class + $\square_7$IsPost

Use library(brms) to make the model (default priors are all flat):

```
```{r}
model_flat <- brm(Sentence.Years ~ Age + Sex + IsWhite + Veteran.Status + IsReturn + Crime.Class + IsPost,
         data = train,
         family=brmsfamily("gaussian"),
         save_all_pars=TRUE,
         chains = 3,
         cores = 1,
         iter = 2000,
         silent=FALSE)
summary(model_flat)
```
```

prior	class	coef
(flat)	b	
(flat)	b	Age
(flat)	b	Crime.Class
(flat)	b	IsPost
(flat)	b	IsReturn
(flat)	b	IsWhite
(flat)	b	SexMale
(flat)	b	Veteran.StatusYes

Prior Selection

Model weak (Normal(0, 100/1.96)):

```r
```{r}
# Fit the model using brm() with custom priors
model_weak <- brm(Sentence.Years ~ Age + Sex + IsWhite + Veteran.Status + Crime.Class + IsPost,
                  data = train,
                  family = brmsfamily("gaussian"),
                  prior = prior(normal(0, 100/1.96), class = 'b'),
                  save_all_pars = TRUE,
                  chains = 3,
                  cores = 1,
                  iter = 1000,
                  silent = FALSE)
```
```

```
               prior class               coef
normal(0, 100/1.96)     b
normal(0, 100/1.96)     b                Age
normal(0, 100/1.96)     b        Crime.Class
normal(0, 100/1.96)     b             IsPost
normal(0, 100/1.96)     b            IsWhite
normal(0, 100/1.96)     b            SexMale
normal(0, 100/1.96)     b  Veteran.StatusYes
```

Model with Scale Invariant Prior (Cauchy(0, 2.5)):

```r
# Model bayes with scale_invariant_prior
prior_scale_invariant <- set_prior("cauchy(0, 2.5)", class = "b")
model_scale_invariant_prior <- brm(Sentence.Years ~ Age + Sex + IsWhite + Veteran.Status + IsReturn +
Crime.Class + IsPost,
         data = train,
         family = brmsfamily("gaussian"),
         prior = prior_scale_invariant,
         save_all_pars = TRUE,
         chains = 3,
         cores = 1,
         iter = 2000,
         silent=FALSE)
```

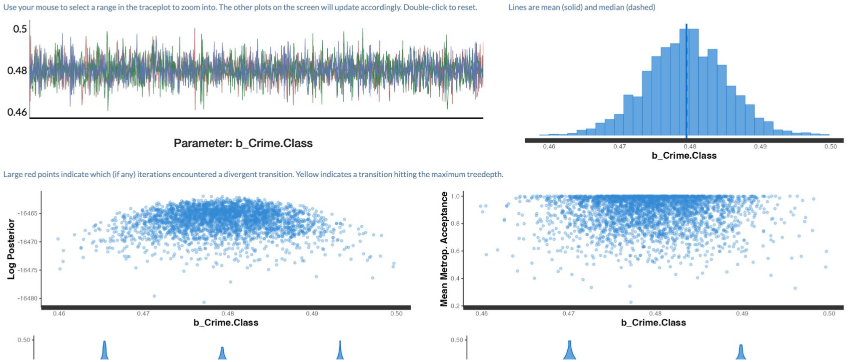
```
          prior class               coef
cauchy(0, 2.5)     b
cauchy(0, 2.5)     b                Age
cauchy(0, 2.5)     b        Crime.Class
cauchy(0, 2.5)     b             IsPost
cauchy(0, 2.5)     b           IsReturn
cauchy(0, 2.5)     b            IsWhite
cauchy(0, 2.5)     b            SexMale
cauchy(0, 2.5)     b  Veteran.StatusYes
```

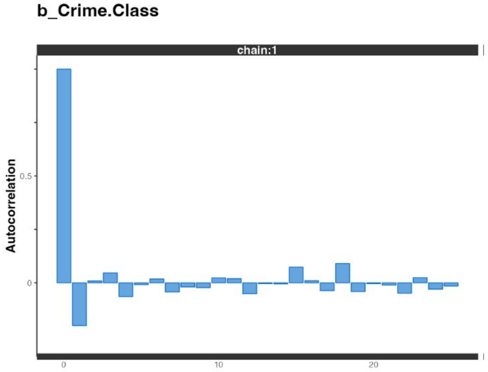
Data Visualization

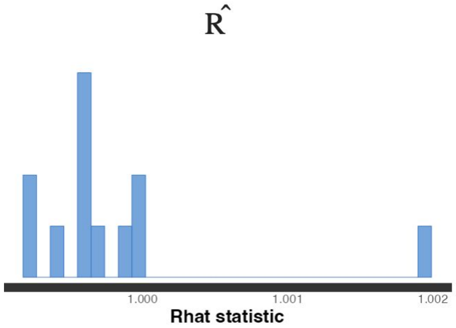
Use library(shinystan)

Model Diagnostics

Model-Flat:

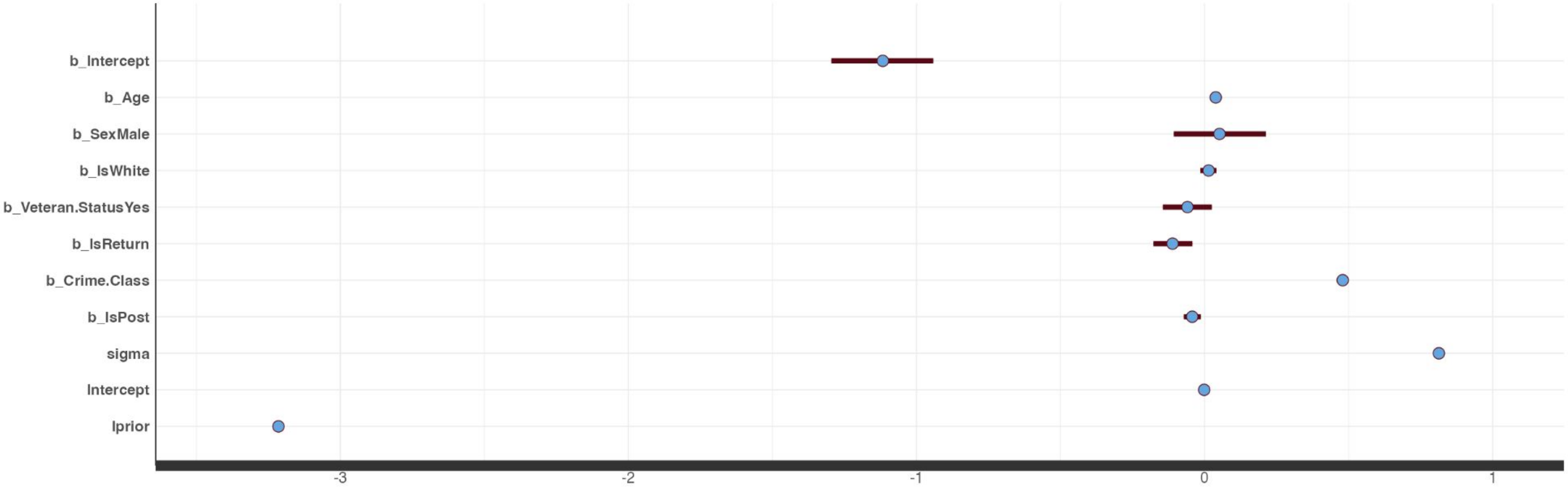






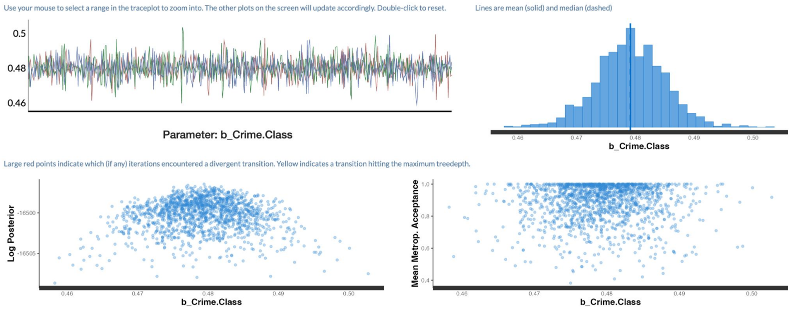
Parameters are converged with low iterations (Trace plot, Gelman diagram converge immediately, Rhat(psrf) < 1.1).
Model is **reliable**.

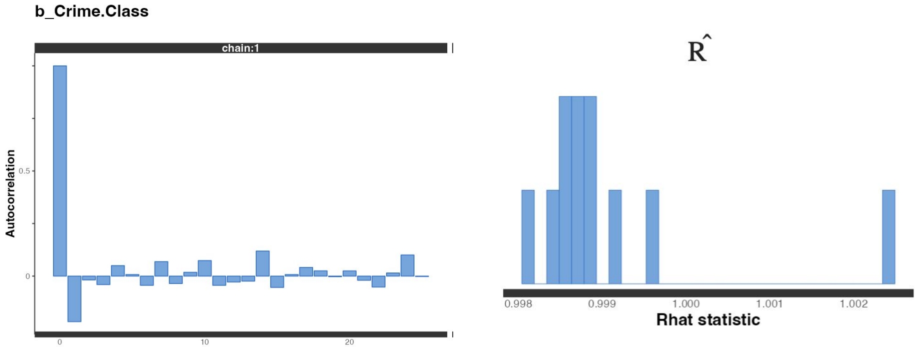
Parameter Plot (each □)



Parameters (Crime.Class, IsReturn, Veteran.Status, sexMale) are significant.

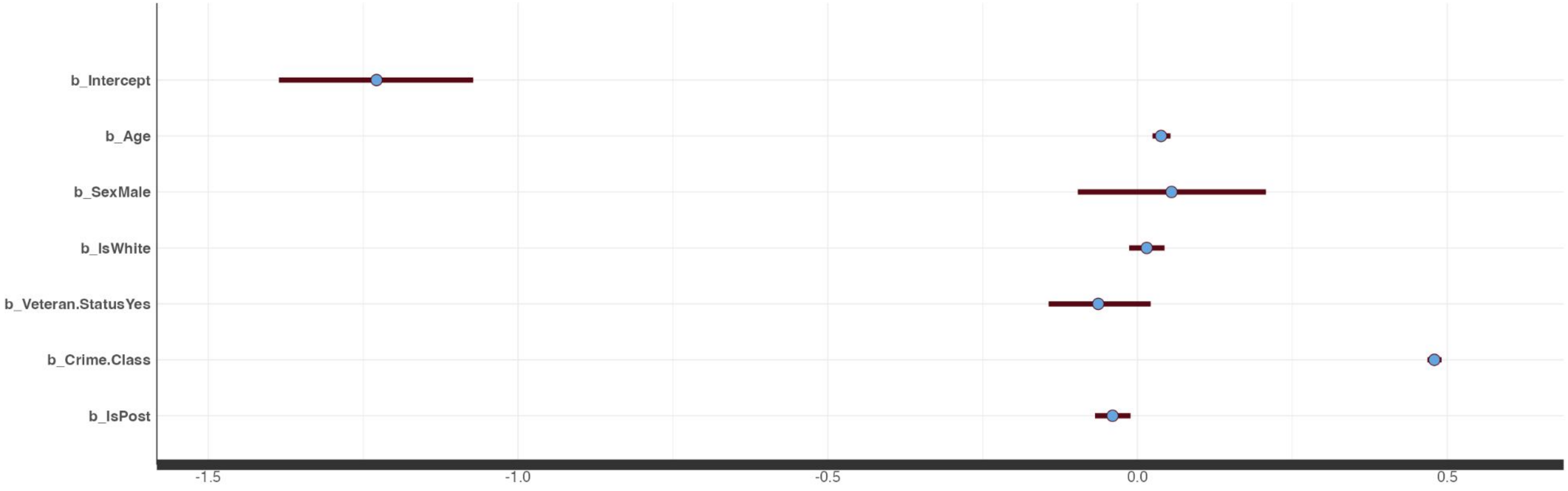
Model-Weak





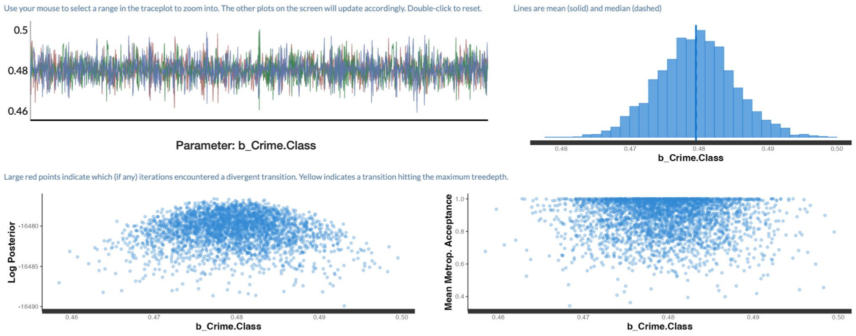
Parameters are converged with low iterations (Trace plot, Gelman diagram converge immediately, Rhat(psrf) < 1.1).
Model is **reliable.**

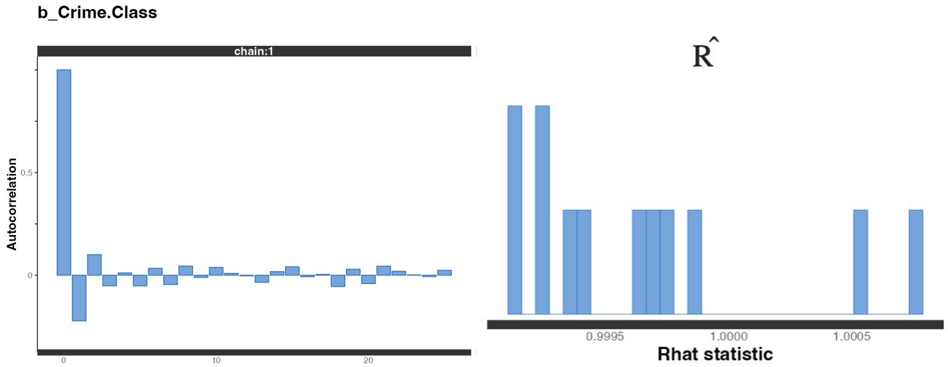
Parameter Plot (each □)



Parameters (Crime.Class, IsReturn, Veteran.Status, sexMale) are significant.

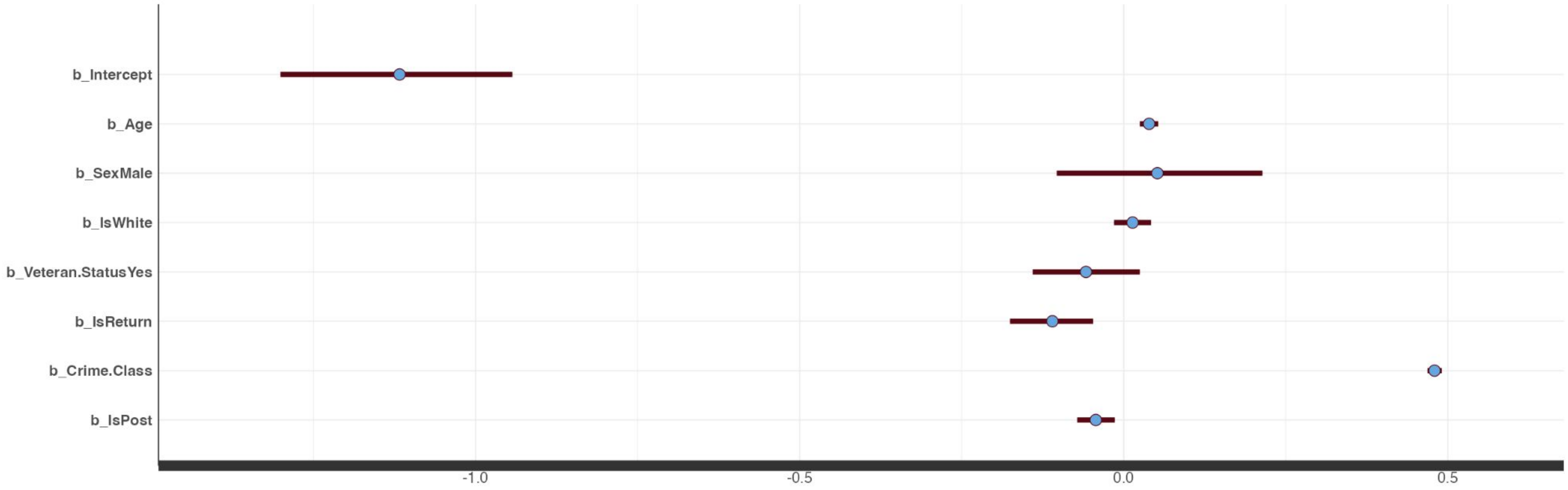
Model-Scale-Invariant-Prior





Parameters are converged with low iterations (Trace plot, Gelman diagram converge immediately, Rhat(psrf) < 1.1).
Model is **reliable**.

Parameter Plot (each □)



Parameters (Crime.Class, IsReturn, Veteran.Status, sexMale) are significant.

The above three models shows **similar** results.

Model Interpretation

Residual sum of squares:

```{r}
pred_flat <- predict(object = model_flat, newdata=test)
pred_weak <- predict(object = model_weak, newdata=test)
pred_scale_invariant_prior <- predict(object = model_scale_invariant_prior, newdata=test)
```

```{r}
#residuals = test$Sentence.Years - pred[,1]
rss_flat = sum((test$Sentence.Years- pred_flat[,1])^2)
rss_weak = sum((test$Sentence.Years- pred_weak[,1])^2)
rss_scale_invariant_prior = sum((test$Sentence.Years- pred_scale_invariant_prior[,1])^2)
rss_flat
rss_weak
rss_scale_invariant_prior
```

```
[1] 2119.469
[1] 2120.491
[1] 2120.463
```

Model Interpretation

Bayes Factor:

Posterior probability ratio between a full model and a reduced model which has the variable dropped.

Variable <chr>	BayesFactor <chr>	DIrection <chr>
Age	47070.3946293848	FALSE
Sex	0.248512282570664	FALSE
IsWhite	0.0553302982993939	FALSE
Veteran.Status	0.283339968085672	FALSE
IsReturn	19.780387959341	FALSE
Crime.Class	Inf	FALSE
IsPost	2.22668667163926	FALSE

Crime.Class is most significant
Then, is Age, IsReturn, IsPost

Model Interpretation

Hypothesis Testing:

Bayesian p-value for null hypothesis

Hypothesis_gt0_flat on posterior parameter □ >= 0

	Hypothesis	Estimate	Est.Error	CI.Lower	CI.Upper	Evid.Ratio	Post.Prob	Star
2	(Age) > 0	0.03910055	0.007523735	0.02706302	0.052103965	Inf	1.00000000	*
7	(Crime.Class) > 0	0.47944471	0.005777424	0.47002609	0.488836314	Inf	1.00000000	*
4	(IsWhite) > 0	0.01359469	0.014298983	-0.01027233	0.036805693	4.825242718	0.82833333	
3	(SexMale) > 0	0.05305140	0.081593084	-0.08003558	0.190267111	2.811944091	0.73766667	
5	(Veteran.StatusYes) > 0	-0.06000455	0.043435202	-0.13038870	0.009846626	0.083815029	0.07733333	
8	(IsPost) > 0	-0.04279596	0.014922774	-0.06734570	-0.018273478	0.002004008	0.00200000	
6	(IsReturn) > 0	-0.11080885	0.034357145	-0.16769819	-0.053252717	0.001001001	0.00100000	
1	(Intercept) > 0	-1.11794297	0.089057765	-1.26728496	-0.972837350	0.000000000	0.00000000	

Hypothesis_le0_flat on posterior parameter □ < 0

	Hypothesis	Estimate	Est.Error	CI.Lower	CI.Upper	Evid.Ratio	Post.Prob	Star
1	(Intercept) < 0	-1.11794297	0.089057765	-1.26728496	-0.972837350	Inf	1.0000000	*
6	(IsReturn) < 0	-0.11080885	0.034357145	-0.16769819	-0.053252717	999.0000000	0.9990000	*
8	(IsPost) < 0	-0.04279596	0.014922774	-0.06734570	-0.018273478	499.0000000	0.9980000	*
5	(Veteran.StatusYes) < 0	-0.06000455	0.043435202	-0.13038870	0.009846626	11.9310345	0.9226667	
3	(SexMale) < 0	0.05305140	0.081593084	-0.08003558	0.190267111	0.3556258	0.2623333	
4	(IsWhite) < 0	0.01359469	0.014298983	-0.01027233	0.036805693	0.2072435	0.1716667	
2	(Age) < 0	0.03910055	0.007523735	0.02706302	0.052103965	0.0000000	0.0000000	
7	(Crime.Class) < 0	0.47944471	0.005777424	0.47002609	0.488836314	0.0000000	0.0000000	

Hypothesis_gt0_flat shows that Age, Crime Class have positive influence on Sentence Year.
Hypothesis_le0_flat shows that IsReturn, IsPost have negative influence on Sentence Year.

Bayesian Model (Interaction Effect)

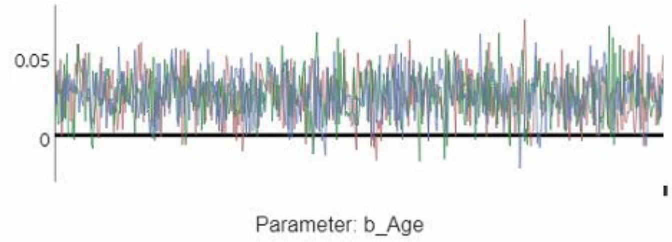
Interaction Model Formula:

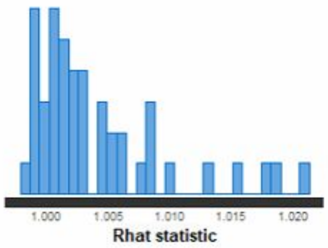
Sentence Year = β_0 + β_1Age + β_2Sex + β_3IsWhite + β_4Veteran.Status + β_5IsReturn + β_6Crime.Class + β_7IsPost + β_8Crime.Class:Age + β_9Crime.Class:Sex + β_{10}Crime.Class:IsWhite + β_{11}Crime.Class:Veteran.Status + β_{12}Crime.Class:IsPost + β_{13}Crime.Class:IsReturn

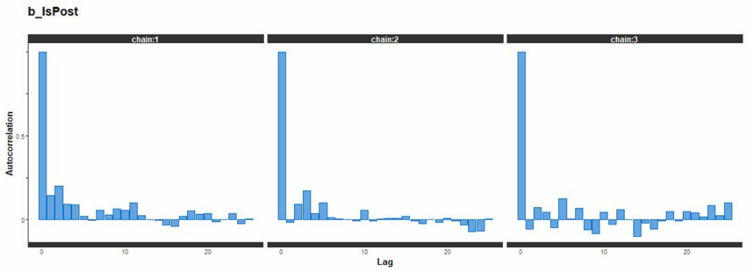
Warning: Is this an issue?

```
Warning: There were 5 divergent transitions after warmup.
```

Diagnosis:







About Horseshoe Prior

Goal: Auto variable selection

Mechanism:

$$\beta_j \mid \lambda_j, \tau \sim \mathrm{N}(0, \lambda_j^2 \tau^2),$$
$$\lambda_j \sim \mathrm{C}^+(0,1), \quad j = 1, \ldots, D.$$

Then, assuming no multicollinearity issue,

$$\bar{\beta}_j = (1-\kappa_j)\hat{\beta}_j$$

$$\kappa_j = \frac{1}{1 + n\sigma^{-2}\tau^2\lambda_j^2}$$

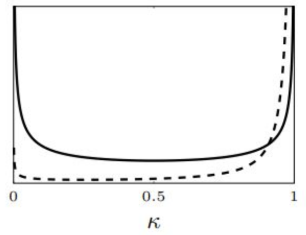


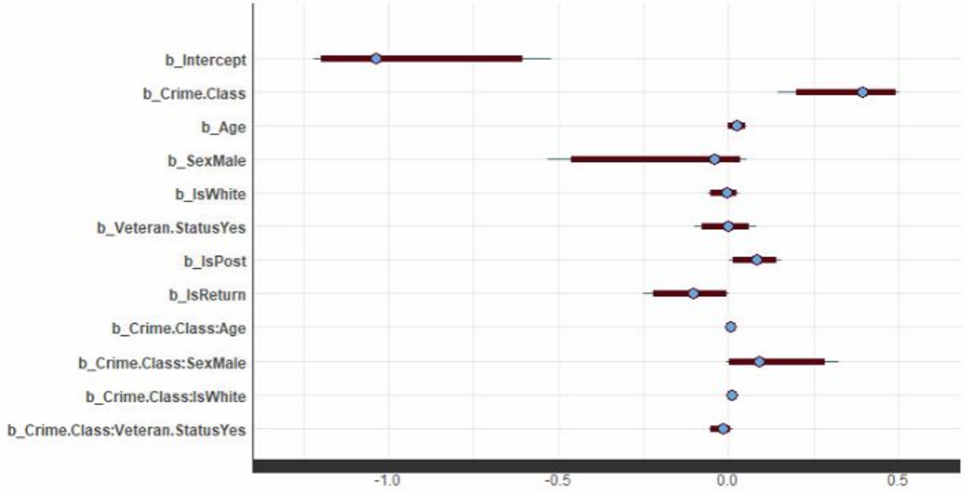
Figure 1: Density for the shrinkage factor (5) for the horseshoe prior (3) when $n\sigma^{-2}\tau^2 = 1$ (solid) and when $n\sigma^{-2}\tau^2 = 0.1$ (dashed).

Model Interpretation

Bayes Factor:

Variable <chr>	BayesFactor <chr>	DIrection <chr>
Crime.Class	Inf	FALSE
Age	47066.6830403309	FALSE
Sex	0.248458989643786	FALSE
IsWhite	0.0555582848588623	FALSE
Veteran.Status	0.284667902901765	FALSE
IsPost	2.25266593860035	FALSE
IsReturn	19.7945041244397	FALSE

Mode Summary:



Model Interpretation

Hypothesis Testing:

Hypothesis	Estimate	Est.Error	CI.Lower	CI.Upper	Evid.Ratio	Post.Prob
(Intercept) < 0	-0.985	0.185	-1.198	-0.6	Inf	1
(IsReturn) < 0	-0.105	0.066	-0.221	-0.0035	25.315	0.962
(Crime.Class:IsPost) < 0	-0.052	0.013	-0.074	-0.028	Inf	1
(Crime.Class) > 0	0.373	0.094	0.199	0.492	374	0.997
(Age) > 0	0.025	0.014	0.001	0.049	24	0.96
(IsPost) > 0	0.081	0.038	0.014	0.143	70.428	0.986
(Crime.Class:SexMale) > 0	0.112	0.089	0.001	0.283	23.193	0.958

Conclusion

For the Bayesian model with only the main effects, using the flat, weak, and scale-invariant priors yielded similar results:

(1) Models converge well, and all parameters quickly achieve a Gelman-Rubin R statistic below 1.1.

(2) Crime class, admission type (new admission vs. return admission), veteran status, and sex are significant predictors in the models.

(3) The older the inmates and the more severe the crime type are associated with more sentence years.

(4) Surprisingly, return admission is more likely to decrease the sentence years compared to new admission.

(5) After the outbreak of the Covid-19 pandemic, there has been a significant decrease in the length of sentence years compared to before the Covid-19 pandemic.

Conclusion

For the Bayesian model with the main effects and interactions:

(1) Similar to our previous findings, return admission is more likely to decrease sentence years than new admission.

(2) Similar to our previous findings, the older the inmates and the more severe the crime type are associated with more sentence years.

(3) Similar to our previous findings, after the outbreak of the Covid-19 pandemic, there has been a significant decrease in the length of sentence years compared to before the Covid-19 pandemic.

Conclusion

For the Bayesian model with the main effects and interactions:

(4) Based on the Bayes factor, crime class is the most significant predictor in the model, followed by age, admission type (New Admission vs. Return Admission), and the Covid-19 pandemic indicator (pre-Covid-19 pandemic vs. after-Covid-19 pandemic).

(5) It is worth noting that the interaction terms are significant between crime class and the Covid-19 pandemic indicator, as well as between crime class and sex, indicating that while crime class has the largest influence on sentence years, such influence was affected by sex and the Covid-19 pandemic.

Limitations

- Multi-category variables are forced into binary to avoid non-convergence issues, thus losing some information.

  By increasing interaction or using a different sampler, we may be able to introduce multi-level categorical variables into regression model.

- There are literature directing the choice of horseshoe shrinkage parameters. By adjusting the shrinkage power, we may be able to explore more interaction effects in a sparse model.

Audience and Future Directions

For criminal justice system stakeholders, including attorney, court/judges, policy decision makers, governments and institutions:

(1) By investigating the combined effects of demographics, criminal justice-related variables, and the Covid-19 pandemic on the length of the sentence years for inmates, we found that demographics such as age and sex, criminal justice-related variables such as admission type and crime class, as well as the Covid-19 pandemic have a great influence on the sentence years.

(2) These information helps identify potential areas for future intervention and improvement, eg, possible age and sex discriminations in determining the sentence years, the reasons behind shorter sentence length instead of longer for return admission, advantages and disadvantages of the decreased sentence length after the pandemic, etc.

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