MA 678 Midterm Project

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Quick Notes (not for final report) Things I'm still working on: - Making the figures more presentable. I know that some of the titles are strangely placed, and I'll fix that for the final report.
- Fixing the placement of figures and tables
- Completing the appendix

Abstract

Spinal cord injuries (SCI) are costly and lifelong medical conditions. The first weeks and months after an injury are crucial to recovery, but many variables impact the timeline of patient recovery. Both hospitals and patients can benefit from an accurate prediction of length of stay. In the following analysis, I have modeled the days spent hospitalized in inpatient rehabilitation following an injury using a fixed effect linear model and then a multi-level linear model. Ovarall, although still imperfect, the mixed effect model is more effective and accurate.

Introduction

Spinal cord injuries (SCI) can be an extremely serious condition where the spinal cord is damaged and has a decreased ability to send and receive nerve signals. Symptoms can include paralysis, pain or pressure in head, neck, or back, weakness and/or inability to move any part of the body, and difficulty breathing (Mayo Clinic, 2021). In the United States, in 2021, it is estimated that there are approximately 54 cases of SCI per 1 million (Jain et al., 2015). The spinal cord is divided into neurological segments. For analysis, the cervical and thoracic segments have been selected. Please refer to the appendix for a diagram of the spinal cord for reference. Each segment roughly corresponds to muscle groups and functions, and damage at a higher level likely indicates more serious impairment. For example, if there is an injury at the C4 level, the individual likely will have weak deltoids (in the shoulder region) and reduced strength and sensation everywhere below this region (Young, 2021).

Since 1973 the National Spinal Cord Injury Model Systems have been collecting data in a database. The database is well managed and extensively documented. The data come from 29 facilities across the United States. The database includes information on 32,159 individuals from 1972 to 2016 and includes a variety of fields which include, for example, injury year, age at injury, sex, use of mechanical ventilation, functional independence scores, ASIA motor index scores, and ASIA sensory scores. This report focus on the modeling the number of days that a patient is hospitalized in inpatient rehabilitation. This is the time after a patient has been treated medically/surgically and before they are discharged from care. This information is relevant to hospitals, so they are able to plan treatment for patients and estimate the number of patients they can care for in a given time. This information is also relevant to patients and their families, so they can also plan the next steps in the patient's recovery.

Methods

First, I selected relevant variables which are listed in the table.

Although the dataset was well organized and documented, I removed missing values and completed some centering, scaling, and recoding of variables. Any modifications can be found in the `clean_data.R` file, and brief notes are listed in the table. I selected cervical and thoracic injuries, since there were 607 lumbar injuries and 9 sacral injuries listed, and there are 4582 and 2510 cervical and thoracic injuries in the complete data set. In addition, individuals 0-14y were excluded from the analysis due to a high volume of missing data. After removing the missing data and the excluded variables, the dataset includes 5104 individuals with injuries from 2006 to 2016. Next, I fit a random effect model to predict log(days hospitalized in inpatient rehab) with a random intercept based on neurologic level of injury and a random slope for the vertebral injury variable also based on neurologic level of injury. I anticipate that the level of injury will impact the "baseline" of days hospitalized and different levels of injury would also have a

Variable	Definition	Notes
Total days inpatient rehab	Total length of stay in inpatient acute/subacute rehabilitation unit until discharge, only days for which charges are incurred	log transformed
Days from injury to rehab admission	Number of days from the date of injury to the first admission to the inpatient rehab unit	log transformed
BMI	Calculated from provided height and weight. weight (lb) / [height (in)]^2 x 703	centered at 0 and scaled by st.dev
Age at injury	Age of patient (years) on the date the SCI occurred	categorical
Use of mechanical ventilation	Any use of mechanical ventilation used to sustain respiration at admission to rehab	recoded to be binary (1 = yes, any type of ventilation. 0 = no)
Vertebral injury	Was there a spinal fracture and/or dislocation in addition to the SCI	binary (1 = yes. 0 = no)
Neurologic level of injury	The highest point on the spine where normal sensory and motor function can be identified at admission to rehab.	Categorical. Selected C01-C08 and T01-T12 for analysis

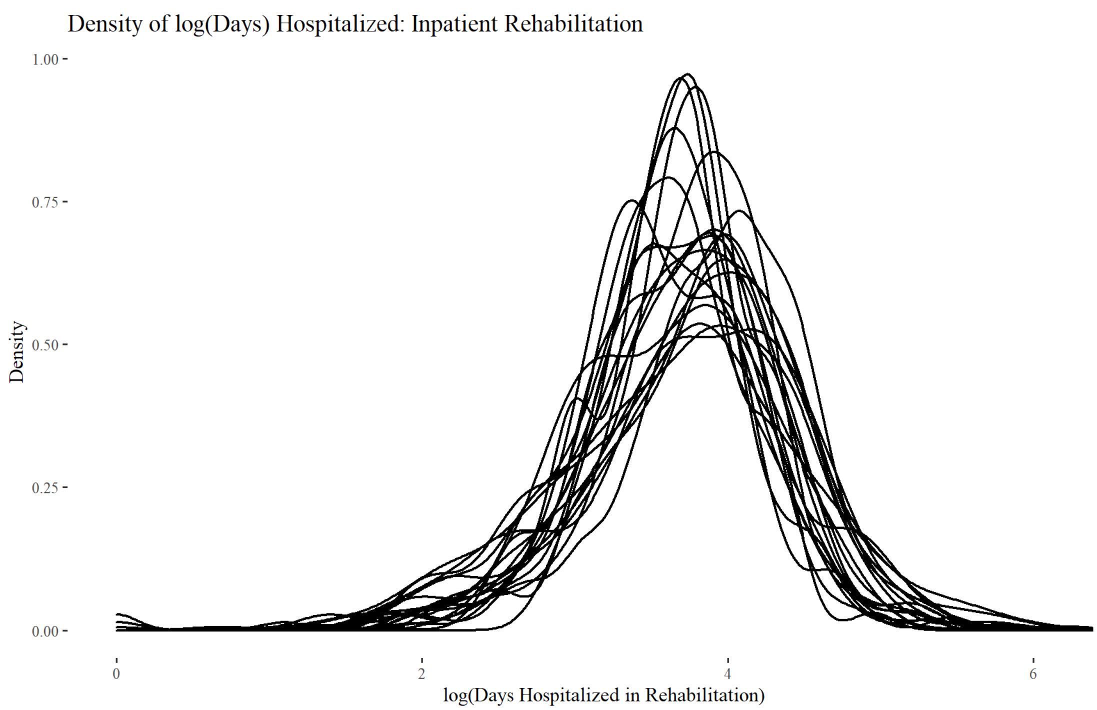

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Figure 1: Density of log(days) hospitalized in inpatient acute and subacute rehabilitation unit. This excludes individuals who were never admitted either due to recovery or death. Each line represents a distribution of log days for a given neurologic level of injury.

Injury Level	Mean log(days)	Std.Dev. log(days)	Mean days	Std.Dev. days
C01	4.03	0.51	63.78	34.1
C04	4.03	0.51	63.95	34.99
C07	4.17	0.55	75.23	46.32
T01	4.15	0.54	73.52	42.53
T04	4.25	0.54	81.41	47.21
T10	4.2	0.52	76.76	43.22

varied impact on the influence of an additional injury on the log(days hospitalized in inpatient rehab). The models were evaluated using posterior predictive checks and leave-one-out validataion (loo).

Results

Exploratory Data Analysis

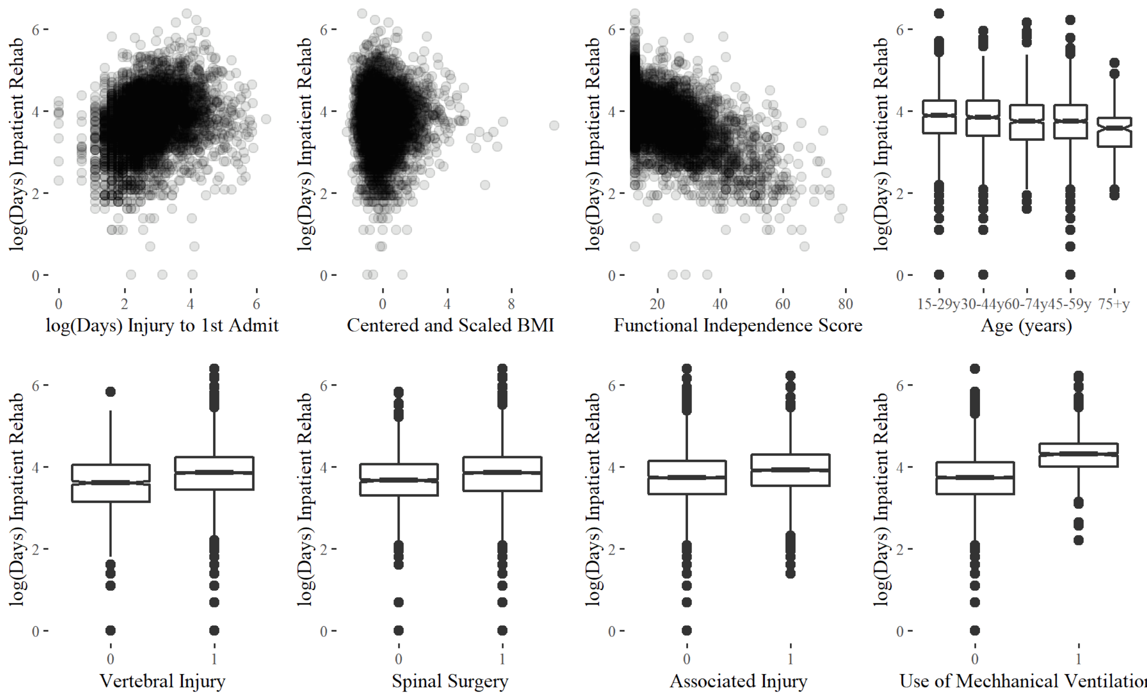

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Figure 2: Selected variables compared to log(days) hospitalized in inpatient rehab.

Models

As mentioned, I fit to models to examine the differences between the fixed effect model and the random effect model. For both, I used the package Stan to use bayesian methods for the regression. Below are figures that summarize the models.

A leave one out cross validation that compares the fixed effect model and the random effect model shows that the random effect model is a better fit based on an ELPD value that is 20 points higher than the fixed effect model. The ELPD is the theoretical expected log point-wise predictive density of the model. The `p_loo` value returned from the validation indicates the number of "effective parameters." In the random effect model, approximately 85% (44/52) of the parameters are effective while in the fixed effect model, the `p_loo` value is larger than the number of parameters that were estimated which indicates weak predictive power of the model.

Using posterior prediction, I have predicted the estimated log(days hospitalized in inpatient rehab) for a patient with average or most common features and different levels of injury. The features were as follows: Independence Score = 13; Log days from injury to first hospital admission = 2.7; Standardized BMI = 0; Age = 15-19y; Ventilator use = 0; Vertebral injury = 1; Associated injury = 0; Spinal surgery = 1; Neurological level of injury = C01, C04, C07, T01, T04, T10.

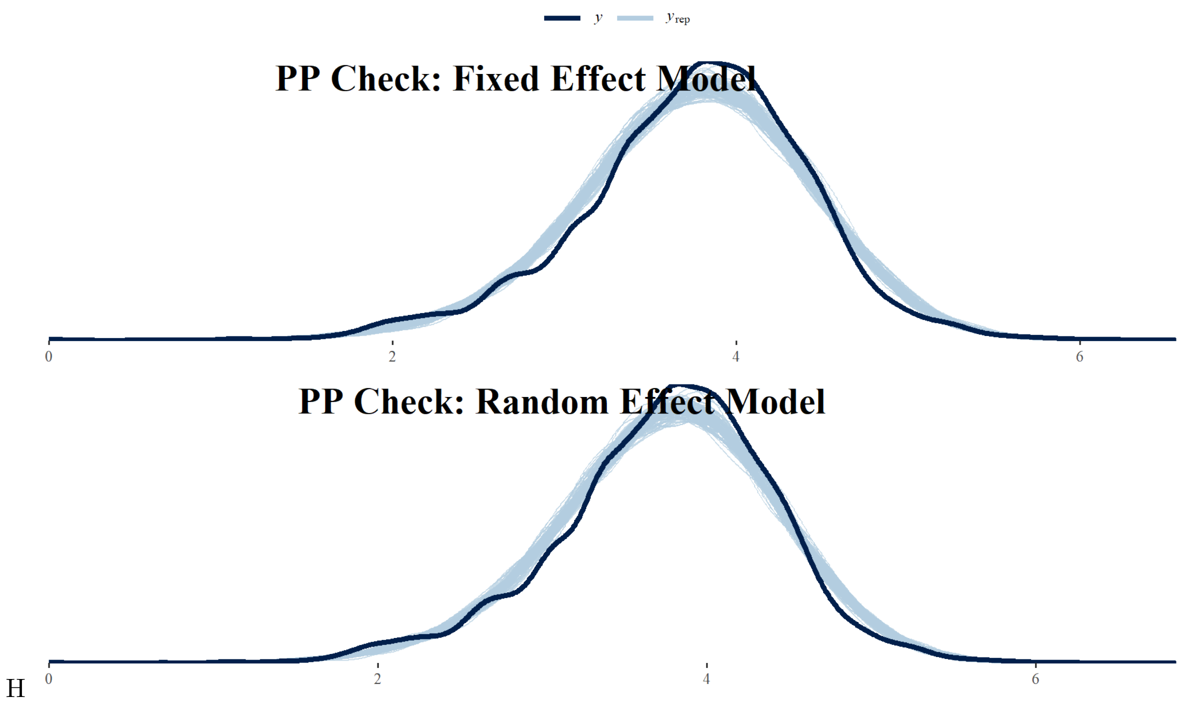

Figure 3: Each plot shows the distribution of the response variable log(days) and the distribution of the 100 posterior predicted responses. Both models seem to approximate the distribution well.

Discussion

In the random effect model, there were several elements that were surprising and should be investigated further. It was surprising to that patients with lower levels of injury (less of their body is impacted) were predicted to have longer stays. Maybe this is because they have more function, so there are more areas where they can improve and progress, while individuals with high levels of injuries are more limited. It should also be noted that these estimations also have large standard deviations which indicate a larger degree of uncertainty. Additionally, I was not expecting that individuals in the 75+ age group would have a shorter duration of rehab hospitalization. Perhaps this is due to a lack of data for this population. SCIs are most common in young people, and in the dataset used for the models less than 5% of patients were in the 75+ group.

Works Cited

Chen, Yuying. National Spinal Cord Injury Model Systems Database. Version 2016ARPublic. Birmingham, AL: National Spinal Cord Injury Statistical Center [distributor]. https://doi.org/10.17605/OSF.IO/NP24C. Accessed 28 October 2021.

Jain, N. B., Ayers, G. D., Peterson, E. N., Harris, M. B., Morse, L., O'Connor, K. C., & Garshick, E. (2015). Traumatic Spinal Cord Injury in the United States, 1993–2012. JAMA, 313(22), 2236–2243. https://doi.org/10.1001/jama.2015.6250

Spinal cord injury—Symptoms and causes. (October 2, 2021). Mayo Clinic. Retrieved November 19, 2021, from https://www.mayoclinic.org/diseases-conditions/spinal-cord-injury/symptoms-causes/syc-20377890

Young, Wise (2021). Spinal Cord Injury Levels & Classification. Travis Roy Foundation. Retrieved November 29, 2021 from https://www.travisroyfoundation.org/sci/resources/spinal-cord-injury-levels-classification/

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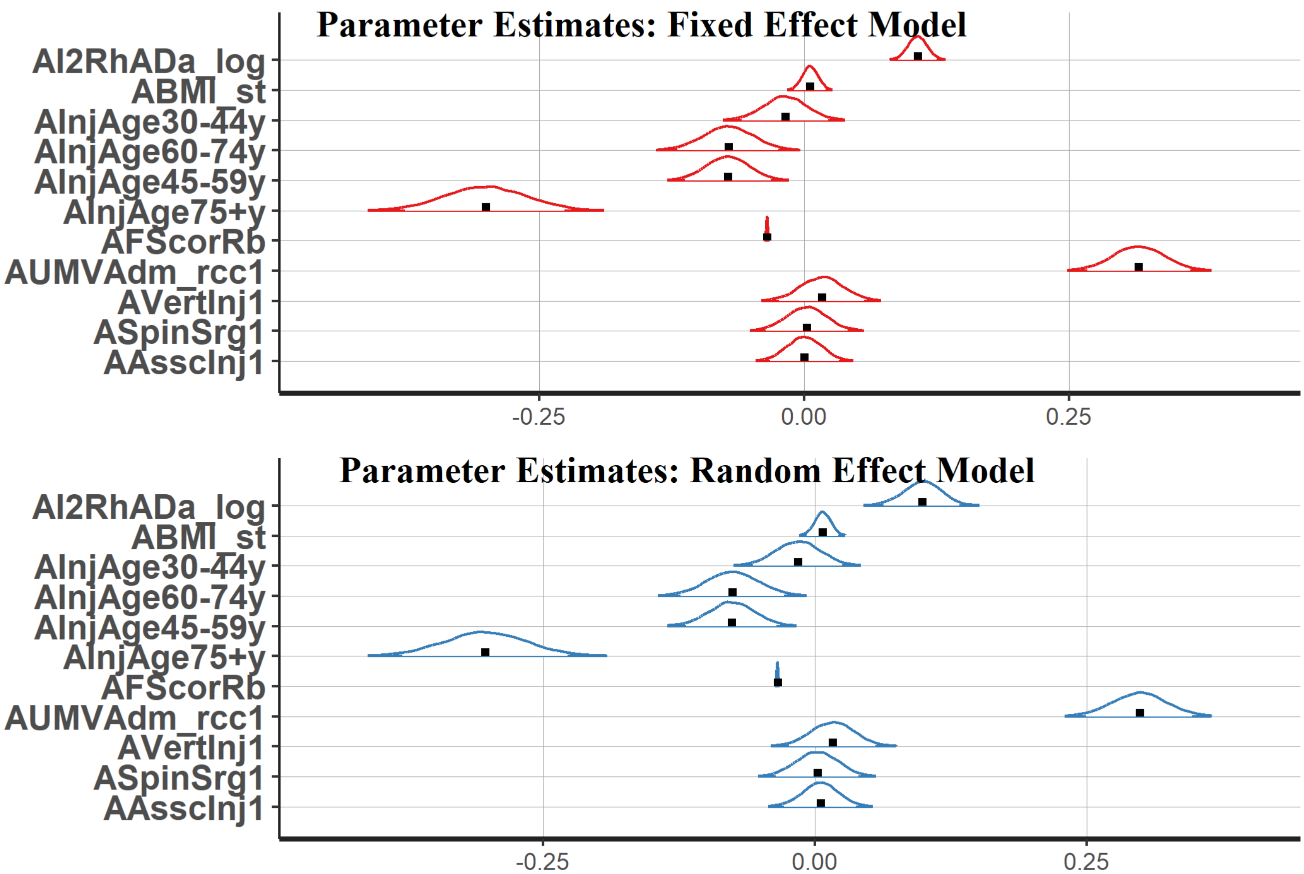
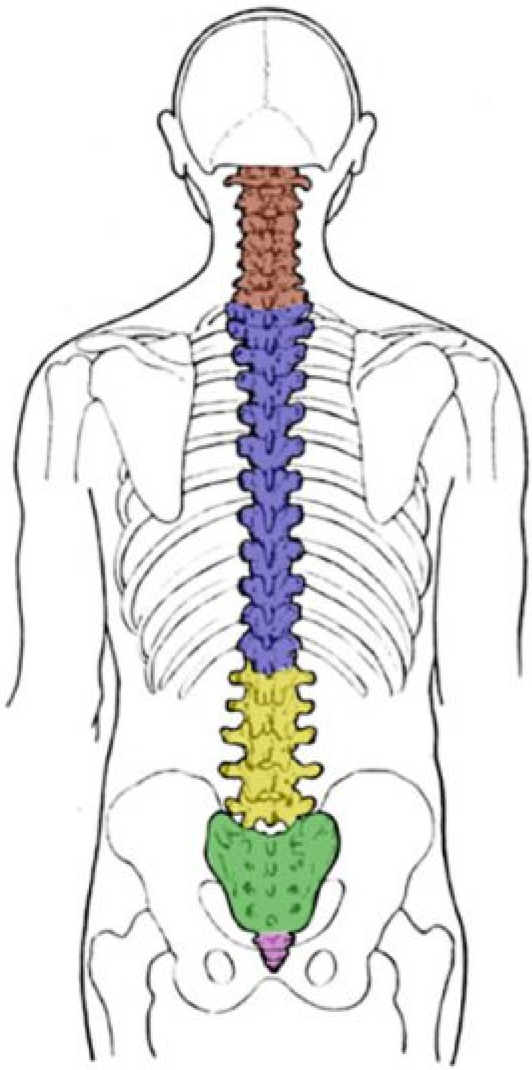
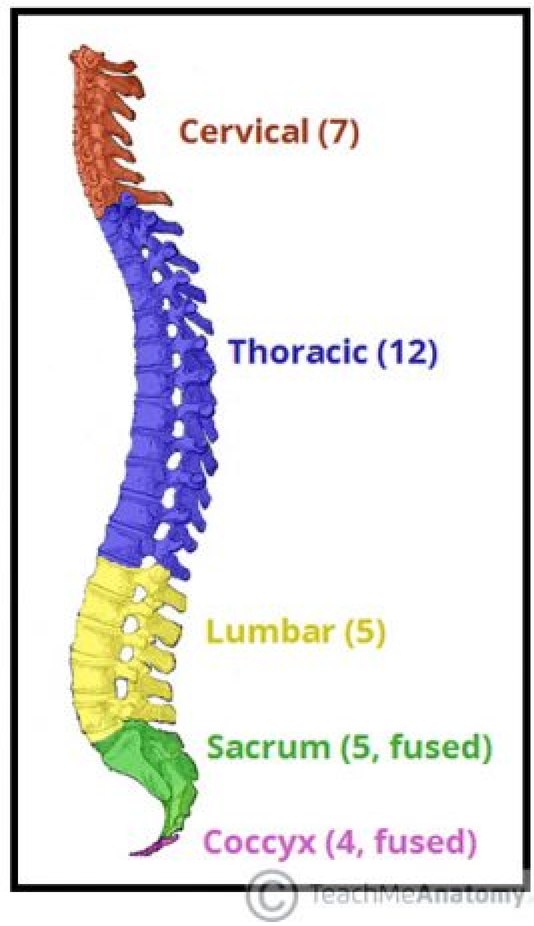


Figure 4: Each plot shows the parameter estimate and density for the nine parameters that are fit in both models. The parameter estimates are largely similar for both models. Interestingly, the estimate for those 75 and older is negative, so individuals in this group spend less time in rehabilitation than someone who is 15-29 years old. It also seems that spinal surgery and associated injuries do not play a strong role in the length of time in rehab.




Cervical (7)
Thoracic (12)
Lumbar (5)
Sacrum (5, fused)
Coccyx (4, fused)
TeachMeAnatomy

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Appendix:

Spine diagram

Summary of fixed effect model

```
##
## Model Info:
##  function:     stan_glm
##  family:       gaussian [identity]
##  formula:      AHDaSyRb_log ~ AI2RhADa_log + ABMI_st + AInjAge + AFScorRb +
##     AUMVAdm_rcc + AVertInj + ASpinSrg + AAsscInj + ANurLvlR_rcc
##  algorithm:    sampling
##  sample:       12000 (posterior sample size)
##  priors:       see help('prior_summary')
##  observations: 5168
##  predictors:   31
##
## Estimates:
##                  mean   sd   10%   50%   90%
## (Intercept)      4.2    0.1  4.1   4.2   4.2
## AI2RhADa_log     0.1    0.0  0.1   0.1   0.1
## ABMI_st          0.0    0.0  0.0   0.0   0.0
## AInjAge30-44y    0.0    0.0  0.0   0.0   0.0
## AInjAge60-74y   -0.1    0.0 -0.1  -0.1   0.0
## AInjAge45-59y   -0.1    0.0 -0.1  -0.1   0.0
## AInjAge75+y     -0.3    0.0 -0.4  -0.3  -0.3
## AFScorRb         0.0    0.0  0.0   0.0   0.0
## AUMVAdm_rcc1     0.3    0.0  0.3   0.3   0.3
## AVertInj1        0.0    0.0  0.0   0.0   0.0
## ASpinSrg1        0.0    0.0  0.0   0.0   0.0
## AAsscInj1        0.0    0.0  0.0   0.0   0.0
## ANurLvlR_rccC02  0.0    0.0 -0.1   0.0   0.0
## ANurLvlR_rccC03  0.0    0.0 -0.1   0.0   0.1
## ANurLvlR_rccC04  0.0    0.0  0.0   0.0   0.1
## ANurLvlR_rccC05  0.0    0.0 -0.1   0.0   0.0
## ANurLvlR_rccC06  0.1    0.1  0.0   0.1   0.2
## ANurLvlR_rccC07  0.2    0.1  0.1   0.2   0.2
## ANurLvlR_rccC08  0.2    0.1  0.1   0.2   0.3
## ANurLvlR_rccT01  0.2    0.1  0.1   0.2   0.3
## ANurLvlR_rccT02  0.2    0.1  0.1   0.2   0.3
## ANurLvlR_rccT03  0.2    0.1  0.1   0.2   0.3
## ANurLvlR_rccT04  0.3    0.1  0.2   0.3   0.3
## ANurLvlR_rccT05  0.1    0.1  0.0   0.1   0.2
## ANurLvlR_rccT06  0.2    0.1  0.1   0.2   0.2
## ANurLvlR_rccT07  0.2    0.1  0.1   0.2   0.3
## ANurLvlR_rccT08  0.2    0.1  0.1   0.2   0.3
## ANurLvlR_rccT09  0.2    0.1  0.1   0.2   0.3
## ANurLvlR_rccT10  0.2    0.1  0.2   0.2   0.3
## ANurLvlR_rccT11  0.3    0.1  0.2   0.3   0.3
## ANurLvlR_rccT12  0.2    0.1  0.2   0.2   0.3
## sigma            0.5    0.0  0.5   0.5   0.5
##
## Fit Diagnostics:
##           mean   sd   10%   50%   90%
## mean_PPD 3.8    0.0  3.7   3.8   3.8
##
## The mean_ppd is the sample average posterior predictive distribution of the outcome variable (for detai
##
```

```
## MCMC diagnostics
##                 mcse Rhat n_eff
## (Intercept)     0.0  1.0   2253
## AI2RhADa_log    0.0  1.0  13502
## ABMI_st         0.0  1.0  13758
## AInjAge30-44y   0.0  1.0   9946
## AInjAge60-74y   0.0  1.0   8711
## AInjAge45-59y   0.0  1.0   8172
## AInjAge75+y     0.0  1.0  12400
## AFScorRb        0.0  1.0  13196
## AUMVAdm_rcc1    0.0  1.0  12686
## AVertInj1       0.0  1.0  12284
## ASpinSrg1       0.0  1.0  14443
## AAsscInj1       0.0  1.0  14441
## ANurLvlR_rccC02 0.0  1.0   1728
## ANurLvlR_rccC03 0.0  1.0   1487
## ANurLvlR_rccC04 0.0  1.0   1345
## ANurLvlR_rccC05 0.0  1.0   1418
## ANurLvlR_rccC06 0.0  1.0   1746
## ANurLvlR_rccC07 0.0  1.0   2408
## ANurLvlR_rccC08 0.0  1.0   3105
## ANurLvlR_rccT01 0.0  1.0   3256
## ANurLvlR_rccT02 0.0  1.0   2629
## ANurLvlR_rccT03 0.0  1.0   2031
## ANurLvlR_rccT04 0.0  1.0   1978
## ANurLvlR_rccT05 0.0  1.0   2378
## ANurLvlR_rccT06 0.0  1.0   2294
## ANurLvlR_rccT07 0.0  1.0   2682
## ANurLvlR_rccT08 0.0  1.0   2173
## ANurLvlR_rccT09 0.0  1.0   2351
## ANurLvlR_rccT10 0.0  1.0   1735
## ANurLvlR_rccT11 0.0  1.0   2025
## ANurLvlR_rccT12 0.0  1.0   1903
## sigma           0.0  1.0  14913
## mean_PPD        0.0  1.0  13619
## log-posterior   0.1  1.0   4678
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a crude measure of effective sample si
```

Summary of mixed effect model

```
##
## Model Info:
##  function:     stan_lmer
##  family:       gaussian [identity]
##  formula:      AHDaSyRb_log ~ AI2RhADa_log + ABMI_st + AInjAge + AFScorRb +
##     AUMVAdm_rcc + AVertInj + ASpinSrg + AAsscInj + (1 + AI2RhADa_log |
##     ANurLvlR_rcc)
##  algorithm:    sampling
##  sample:       15000 (posterior sample size)
##  priors:       see help('prior_summary')
##  observations: 5149
##  groups:       ANurLvlR_rcc (20)
##
## Estimates:
##                                                   mean   sd   10%   50%   90%
## (Intercept)                                      4.3    0.1  4.2   4.3   4.4
## AI2RhADa_log                                     0.1    0.0  0.1   0.1   0.1
```

```
## ABMI_st                                        0.0    0.0  0.0   0.0   0.0
## AInjAge30-44y                                  0.0    0.0  0.0   0.0   0.0
## AInjAge60-74y                                 -0.1    0.0 -0.1  -0.1   0.0
## AInjAge45-59y                                 -0.1    0.0 -0.1  -0.1   0.0
## AInjAge75+y                                   -0.3    0.0 -0.4  -0.3  -0.3
## AFScorRb                                       0.0    0.0  0.0   0.0   0.0
## AUMVAdm_rcc1                                   0.3    0.0  0.3   0.3   0.3
## AVertInj1                                      0.0    0.0  0.0   0.0   0.0
## ASpinSrg1                                      0.0    0.0  0.0   0.0   0.0
## AAsscInj1                                      0.0    0.0  0.0   0.0   0.0
## b[(Intercept) ANurLvlR_rcc:C01]               -0.3    0.1 -0.4  -0.3  -0.1
## b[AI2RhADa_log ANurLvlR_rcc:C01]               0.1    0.0  0.0   0.1   0.1
## b[(Intercept) ANurLvlR_rcc:C02]               -0.4    0.1 -0.5  -0.4  -0.3
## b[AI2RhADa_log ANurLvlR_rcc:C02]               0.1    0.0  0.1   0.1   0.1
## b[(Intercept) ANurLvlR_rcc:C03]               -0.2    0.1 -0.3  -0.2   0.0
## b[AI2RhADa_log ANurLvlR_rcc:C03]               0.0    0.0  0.0   0.0   0.1
## b[(Intercept) ANurLvlR_rcc:C04]                0.0    0.1 -0.1   0.0   0.1
## b[AI2RhADa_log ANurLvlR_rcc:C04]               0.0    0.0 -0.1   0.0   0.0
## b[(Intercept) ANurLvlR_rcc:C05]               -0.4    0.1 -0.5  -0.4  -0.3
## b[AI2RhADa_log ANurLvlR_rcc:C05]               0.1    0.0  0.1   0.1   0.1
## b[(Intercept) ANurLvlR_rcc:C06]               -0.1    0.1 -0.2  -0.1   0.0
## b[AI2RhADa_log ANurLvlR_rcc:C06]               0.0    0.0  0.0   0.0   0.1
## b[(Intercept) ANurLvlR_rcc:C07]                0.0    0.1 -0.1   0.0   0.2
## b[AI2RhADa_log ANurLvlR_rcc:C07]               0.0    0.0  0.0   0.0   0.0
## b[(Intercept) ANurLvlR_rcc:C08]                0.0    0.2 -0.2   0.0   0.2
## b[AI2RhADa_log ANurLvlR_rcc:C08]               0.0    0.0  0.0   0.0   0.1
## b[(Intercept) ANurLvlR_rcc:T01]                0.1    0.1 -0.1   0.1   0.3
## b[AI2RhADa_log ANurLvlR_rcc:T01]               0.0    0.0 -0.1   0.0   0.0
## b[(Intercept) ANurLvlR_rcc:T02]                0.1    0.1 -0.1   0.1   0.3
## b[AI2RhADa_log ANurLvlR_rcc:T02]               0.0    0.0 -0.1   0.0   0.0
## b[(Intercept) ANurLvlR_rcc:T03]                0.4    0.1  0.2   0.4   0.6
## b[AI2RhADa_log ANurLvlR_rcc:T03]              -0.1    0.0 -0.2  -0.1  -0.1
## b[(Intercept) ANurLvlR_rcc:T04]                0.2    0.1  0.0   0.2   0.4
## b[AI2RhADa_log ANurLvlR_rcc:T04]               0.0    0.0 -0.1   0.0   0.0
## b[(Intercept) ANurLvlR_rcc:T05]               -0.1    0.1 -0.3  -0.1   0.1
## b[AI2RhADa_log ANurLvlR_rcc:T05]               0.0    0.0  0.0   0.0   0.1
## b[(Intercept) ANurLvlR_rcc:T06]                0.1    0.1 -0.1   0.1   0.3
## b[AI2RhADa_log ANurLvlR_rcc:T06]               0.0    0.0 -0.1   0.0   0.0
## b[(Intercept) ANurLvlR_rcc:T07]                0.1    0.1 -0.1   0.1   0.2
## b[AI2RhADa_log ANurLvlR_rcc:T07]               0.0    0.0 -0.1   0.0   0.0
## b[(Intercept) ANurLvlR_rcc:T08]                0.1    0.1 -0.1   0.1   0.3
## b[AI2RhADa_log ANurLvlR_rcc:T08]               0.0    0.0 -0.1   0.0   0.0
## b[(Intercept) ANurLvlR_rcc:T09]                0.0    0.1 -0.1   0.0   0.2
## b[AI2RhADa_log ANurLvlR_rcc:T09]               0.0    0.0 -0.1   0.0   0.0
## b[(Intercept) ANurLvlR_rcc:T10]                0.1    0.1 -0.1   0.1   0.2
## b[AI2RhADa_log ANurLvlR_rcc:T10]               0.0    0.0  0.0   0.0   0.0
## b[(Intercept) ANurLvlR_rcc:T11]                0.2    0.1  0.1   0.2   0.4
## b[AI2RhADa_log ANurLvlR_rcc:T11]               0.0    0.0 -0.1   0.0   0.0
## b[(Intercept) ANurLvlR_rcc:T12]                0.0    0.1 -0.1   0.0   0.1
## b[AI2RhADa_log ANurLvlR_rcc:T12]               0.0    0.0  0.0   0.0   0.1
## sigma                                          0.5    0.0  0.5   0.5   0.5
## Sigma[ANurLvlR_rcc:(Intercept),(Intercept)]    0.1    0.0  0.0   0.0   0.1
## Sigma[ANurLvlR_rcc:AI2RhADa_log,(Intercept)]   0.0    0.0  0.0   0.0   0.0
## Sigma[ANurLvlR_rcc:AI2RhADa_log,AI2RhADa_log]  0.0    0.0  0.0   0.0   0.0
##
## Fit Diagnostics:
##            mean   sd   10%   50%   90%
## mean_PPD 3.8    0.0  3.7   3.8   3.8
```

```
##
## The mean_ppd is the sample average posterior predictive distribution of the outcome variable (for detai
##
## MCMC diagnostics
##                                       mcse Rhat n_eff
## (Intercept)                           0.0  1.0   4705
## AI2RhADa_log                          0.0  1.0   4956
## ABMI_st                               0.0  1.0  18299
## AInjAge30-44y                         0.0  1.0  14072
## AInjAge60-74y                         0.0  1.0  12417
## AInjAge45-59y                         0.0  1.0  11775
## AInjAge75+y                           0.0  1.0  16898
## AFScorRb                              0.0  1.0  16717
## AUMVAdm_rcc1                          0.0  1.0  19952
## AVertInj1                             0.0  1.0  17598
## ASpinSrg1                             0.0  1.0  20257
## AAsscInj1                             0.0  1.0  20296
## b[(Intercept) ANurLvlR_rcc:C01]       0.0  1.0   9731
## b[AI2RhADa_log ANurLvlR_rcc:C01]      0.0  1.0  10886
## b[(Intercept) ANurLvlR_rcc:C02]       0.0  1.0   8610
## b[AI2RhADa_log ANurLvlR_rcc:C02]      0.0  1.0  10463
## b[(Intercept) ANurLvlR_rcc:C03]       0.0  1.0   7078
## b[AI2RhADa_log ANurLvlR_rcc:C03]      0.0  1.0   8727
## b[(Intercept) ANurLvlR_rcc:C04]       0.0  1.0   5646
## b[AI2RhADa_log ANurLvlR_rcc:C04]      0.0  1.0   7156
## b[(Intercept) ANurLvlR_rcc:C05]       0.0  1.0   6558
## b[AI2RhADa_log ANurLvlR_rcc:C05]      0.0  1.0   8505
## b[(Intercept) ANurLvlR_rcc:C06]       0.0  1.0   9115
## b[AI2RhADa_log ANurLvlR_rcc:C06]      0.0  1.0  10647
## b[(Intercept) ANurLvlR_rcc:C07]       0.0  1.0  11675
## b[AI2RhADa_log ANurLvlR_rcc:C07]      0.0  1.0  12707
## b[(Intercept) ANurLvlR_rcc:C08]       0.0  1.0  12810
## b[AI2RhADa_log ANurLvlR_rcc:C08]      0.0  1.0  13107
## b[(Intercept) ANurLvlR_rcc:T01]       0.0  1.0  13875
## b[AI2RhADa_log ANurLvlR_rcc:T01]      0.0  1.0  14045
## b[(Intercept) ANurLvlR_rcc:T02]       0.0  1.0  13108
## b[AI2RhADa_log ANurLvlR_rcc:T02]      0.0  1.0  13566
## b[(Intercept) ANurLvlR_rcc:T03]       0.0  1.0   8792
## b[AI2RhADa_log ANurLvlR_rcc:T03]      0.0  1.0   9107
## b[(Intercept) ANurLvlR_rcc:T04]       0.0  1.0  10509
## b[AI2RhADa_log ANurLvlR_rcc:T04]      0.0  1.0  11507
## b[(Intercept) ANurLvlR_rcc:T05]       0.0  1.0  12628
## b[AI2RhADa_log ANurLvlR_rcc:T05]      0.0  1.0  12569
## b[(Intercept) ANurLvlR_rcc:T06]       0.0  1.0  10377
## b[AI2RhADa_log ANurLvlR_rcc:T06]      0.0  1.0  10689
## b[(Intercept) ANurLvlR_rcc:T07]       0.0  1.0  12634
## b[AI2RhADa_log ANurLvlR_rcc:T07]      0.0  1.0  13351
## b[(Intercept) ANurLvlR_rcc:T08]       0.0  1.0  10065
## b[AI2RhADa_log ANurLvlR_rcc:T08]      0.0  1.0  11317
## b[(Intercept) ANurLvlR_rcc:T09]       0.0  1.0  11063
## b[AI2RhADa_log ANurLvlR_rcc:T09]      0.0  1.0  11885
## b[(Intercept) ANurLvlR_rcc:T10]       0.0  1.0   8595
## b[AI2RhADa_log ANurLvlR_rcc:T10]      0.0  1.0  10253
## b[(Intercept) ANurLvlR_rcc:T11]       0.0  1.0   9547
## b[AI2RhADa_log ANurLvlR_rcc:T11]      0.0  1.0  11177
## b[(Intercept) ANurLvlR_rcc:T12]       0.0  1.0   9025
## b[AI2RhADa_log ANurLvlR_rcc:T12]      0.0  1.0  10411
## sigma                                 0.0  1.0  20871
```

```
## Sigma[ANurLvlR_rcc:(Intercept),(Intercept)]   0.0  1.0   5271
## Sigma[ANurLvlR_rcc:AI2RhADa_log,(Intercept)]  0.0  1.0   5464
## Sigma[ANurLvlR_rcc:AI2RhADa_log,AI2RhADa_log] 0.0  1.0   5644
## mean_PPD                                      0.0  1.0  14645
## log-posterior                                 0.1  1.0   4226
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a crude measure of effective sample si
```

Results/Output of LOO