Report on AQI Bayesian hierarchical modeling

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we build various random effects model with either insurance status (pay) or median income in the home zip code of the patients as primary predictor and added variables like institution or procedure cpt codes as random effects, sometimes nested.

```
## [1] 8
```

```
## stan_glmer(formula = formulaR3.0, data = myAQI, family = binomial,
##     chains = 4, iter = 500, cores = 4)
##
## Algorithm: sampling
## Posterior sample size: 1000
## Observations: 106282
## Groups: cpt 3343, prov 634
##
## Estimates:
##                    mean   sd    2.5%   50%   97.5%
## payMEDICAID      -0.23   0.03 -0.28  -0.23 -0.18
## payMedicare      -0.28   0.03 -0.33  -0.27 -0.23
## paySELF          -0.17   0.09 -0.34  -0.17  0.01
## age_groupUnder 1 -2.60   0.11 -2.83  -2.60 -2.39
## age_group1-18     0.24   0.05  0.14   0.24  0.36
## age_group50 - 64 -0.27   0.03 -0.32  -0.27 -0.21
## age_group65 - 79 -0.32   0.03 -0.38  -0.32 -0.26
## age_group80+     -0.69   0.04 -0.78  -0.69 -0.60
## sexmale          -0.30   0.02 -0.34  -0.30 -0.26
##
## Diagnostics:
##                  mcse Rhat n_eff
## payMEDICAID      0.00 1.00 1000
## payMedicare      0.00 1.00 1000
## paySELF          0.00 1.00 1000
## age_groupUnder 1 0.00 1.00 1000
## age_group1-18    0.00 1.00 1000
## age_group50 - 64 0.00 1.00 1000
## age_group65 - 79 0.00 1.00  844
## age_group80+     0.00 1.00  804
## sexmale          0.00 1.00 1000
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a crude measure of effective sample
```