Bayesian Analysis of Systolic Blood Pressure of Nurses Using a Mixed Effects Model

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Since the United States has a well-established shortage of nurses, the occupation is known to be stressful and intense, leaving them with a lack of time to focus on their own wellbeing. One warning health sign is high systolic blood pressure (SBP), a risk factor for many deadly diseases. Therefore, we examined potential factors that could affect blood pressure for nurses to identify subgroups of nurses more likely to experience higher systolic blood pressure.

The data set used for this analysis includes multiple SBP readings for 203 female nurses who are each assigned a unique subject id number as well as characteristics including family history of hypertension, menstrual cycle phase, and a work indicator indicating whether the corresponding nurse was working on the day of measurement.

Since the data is clearly longitudinal, a mixed effects model with a random intercept was fitted. With *i* indexing nurses from 1 to 203, *j* indexing observations for each nurse from 1 to n_i (the number of observations for the ith nurse), y_{ij} denoting SBP for the jth observation of the ith nurse, $'famhist1'$ indicating that exactly one parent has hypertension and $'famhist2'$ indicating that both parents have hypertension (reference: no parents have hypertension), $'work'$ indicating work status on day of measurement (reference: not working), '*phase*' indicating current phase of menstrual cycle is luteal phase (reference: follicular phase), γ_i denoting the random intercept effect, and σ^2 denoting residual variance, the model is specified as follows: $y_{ij}|\mu_{ij}$, $\sigma^2 \sim N(\mu_{ij}, \sigma^2)$, where $\mu_{ij} = \beta_0 + \beta_1 * famhist1_i + \beta_2 * famhist2_i + \beta_3 * work_{ij} + \beta_4 * phase_{ij} + \beta_5 * famhist1_i * work1_{ij} + \beta_6 * famhist_i * work_{ij} + \gamma_i$. The random intercepts are $\gamma_i|D \sim N(0, D)$.

Normal priors were set for the regression coefficients, and gamma priors were set for the random intercept and residual precisions, yielding inverse gamma priors for the corresponding variances. Since prior information for all parameters except the interaction terms is from past

research studies on different populations, means of the priors were set to the reported means, but the variances were inflated. We used results from an analysis of blood pressure in American adults to determine the intercept prior. Since healthy women had a mean blood pressure of 114 mmHG and a standard deviation of approximately 20 mmHG, we set the corresponding prior as $\beta_0 \sim N_o(114.0, 0.001)$ (Wright et al., 2011). Results from a study on the Chinese elderly comparing blood pressure between family history categories (Liu et al., 2015) was used to set the corresponding family history priors as $\beta_1 \sim N_o(3.2, 0.20)$ and $\beta_2 \sim N_o(5.3, 0.10)$. For working status, prior information was based on a study conducted on 135 Los Angeles nurses comparing blood pressure on workdays and off days (Goldstein et al., 1999) and was set as $\beta_3 \sim N_o(2.6, 1)$. Prior information for menstrual cycle was from a study on 40 Irish women measuring changes in blood pressure during the menstrual cycle, so we set $\beta_4 \sim N_o(0.22, 1.1)$ (Dunne et al., 1991). Since information about interactions between family history and working status could not be found, no interactions were expected but prior variances were high ($\beta_5,\ \beta_6 \sim N_o(0, 0.025)$. The random intercept precision prior was set as $\tau_\gamma \sim (64, 5184)$ by averaging within-groups variances from the study used to create prior for working status (Goldstein et al., 1999), while the residual precision prior was set as $\tau_\epsilon \sim$ gamma (237.25, 14066.525) using results from a study analyzing visit-to-visit variability in SBP (Muntner et al., 2011).

Posterior estimates are reported in Table 1. On average, the intercept, defined as SBP of nurses who did not work and are in the follicular phase of the menstrual cycle on measurement days and do not have a family history of hypertension, is 115.42 mmHG. On average, SBP of nurses with one parent and two parents with hypertension are both higher than those with no family history of hypertension, all else equal, but only effect for two parents with hypertension is significant (P (< 0|Y) = 0.21 for one parent; P (< 0|Y) = 0 for two parents). Therefore, we can

conclude that family history does help predict SBP in this population but only if both parents have hypertension. There are no significant interactions between working status and family history of hypertension (P (< 0|Y) = 0.75, P (> 0|Y) = 0.25) if one parent has hypertension, P (< 0|Y) = 0.50, P (> 0|Y) = 0.50 if both parents do). SBP is significantly higher for nurses on working days than non-working days, (P(> (0|Y) = 1), all else equal. Menstrual cycle phase does not have a significant effect on SBP (P (< 0|Y) = 0.24, P(> 0|Y) = 0.76) after accounting for the effects of all other predictors. On average, standard deviation of the residuals is 12.88 mmHG, and the standard deviation of the random effects is 8.56 mmHG.

Posteriors were plotted for the standard deviations (Figure 1), while both priors and posteriors were plotted for all fixed effects (Figure 2). Both standard deviations appear to be precisely estimated (Figure 1). For the fixed effects, posteriors are all more peaked and narrower than the priors, so posterior estimates are more precise (Figure 2). For the intercept, the prior density is flat in the plausible range of the posterior distribution, so this prior is very weak. The prior mean is higher than the posterior mean for the one-parent family history effect but lower for the two-parent family history effect. Posterior mean is slightly higher than prior mean for working status and cycle phase effects. The posterior mean is slightly smaller than the prior mean for the interaction of one-parent family history with working status but equal for the two-parent family history interaction.

Sensitivity analysis for fixed effects variances prior show that posterior standard deviation is positively associated with prior variance, but the trends in posterior means differ among the fixed effects (Table 2). As for the overall conclusions, one-parent family history effect does become significant at low prior variance (P (< 0|Y = 0.03), so we can conclude that conclusions drawn for this specific effect are highly sensitive to changes in the corresponding prior variance.

References

Dunne, F. P., Barry, D. G., Ferriss, J. B., Grealy, G., & Murphy, D. (1991). Changes in blood pressure during the normal menstrual cycle. *Clinical Science*, *81*(s25), 515–518. https://doi.org/10.1042/cs0810515

Goldstein, I. B., Shapiro, D., Chicz-DeMet, A., & Guthrie, D. (1999). Ambulatory blood pressure, heart rate, and neuroendocrine responses in women nurses during work and off work days. *Psychosomatic Medicine*, *61*(3), 387–396. https://doi.org/10.1097/00006842-199905000-00020

Liu, M., He, Y., Jiang, B., Wang, J., Wu, L., Wang, Y., Zhang, D., Zeng, J., & Yao, Y. (2015). Association between family history and hypertension among Chinese elderly. *Medicine*, *94*(48), e2226. https://doi.org/10.1097/md.0000000000002226

Muntner, P., Shimbo, D., Tonelli, M., Reynolds, K., Arnett, D. K., & Oparil, S. (2011). The relationship between visit-to-visit variability in systolic blood pressure and all-cause mortality in the general population. *Hypertension*, *57*(2), 160–166. https://doi.org/10.1161/hypertensionaha.110.162255

Wright, J. D., Hughes, J. P., Ostchega, Y., Yoon, S. S., & Nwankwo, T. (2011). Mean systolic and diastolic blood pressure in adults aged 18 and over in the United States, 2001 2008. *National health statistics reports*, (35), 1–24.

Appendix

Table 1. Posterior distributions of fixed effects and standard deviations from a mixed effects model of systolic blood pressure of nurses. Beta0-6 represent fixed effects coefficients, Sigma represents standard deviation of the residuals, and sqrtD represents standard deviation of the random intercepts. Posterior means, standard deviations, and 95% credible intervals are presented for each parameter. Posterior probabilities that each parameter is positive and negative are also shown. Abbreviations: CI = credible intervention; P = probability; SD = standard deviation.

Description	Parameter	Mean	SD	[95% CI]	P (< 0|Y)	P (> 0|Y)
Fixed Effects	Beta0	115.42	0.96	[113.59, 117.34]	0	1
	Beta1	1.15	1.40	[-1.61, 3.92]	0.21	0.79
	Beta2	7.36	2.23	[2.93, 11.72]	0	1
	Beta3	3.20	0.84	[1.56, 4.89]	0	1
	Beta4	0.54	0.75	[-0.98, 2.00]	0.24	0.76
	Beta5	-1.24	1.86	[-4.89, 2.45]	0.75	0.25
	Beta6	-0.01	3.43	[-6.74, 6.75]	0.50	0.50
Standard deviations	sigma	12.88	0.09	[12.70, 13.06]	0	1
	sqrtD	8.56	0.35	[7.91, 9.27]	0	1

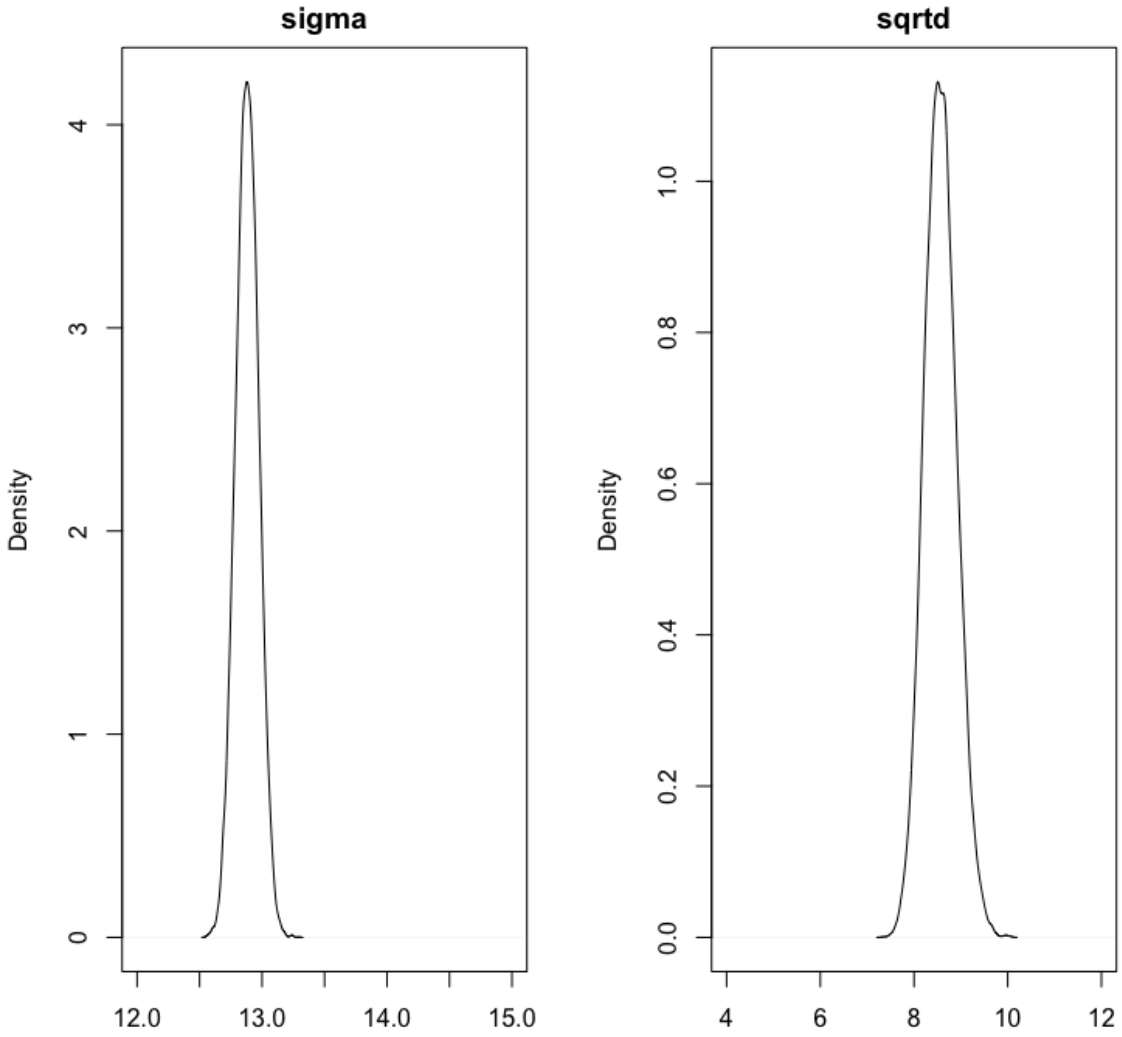

Figure 1. Posterior densities of residual standard deviation (sigma) and random intercept standard deviation (sqrtD).

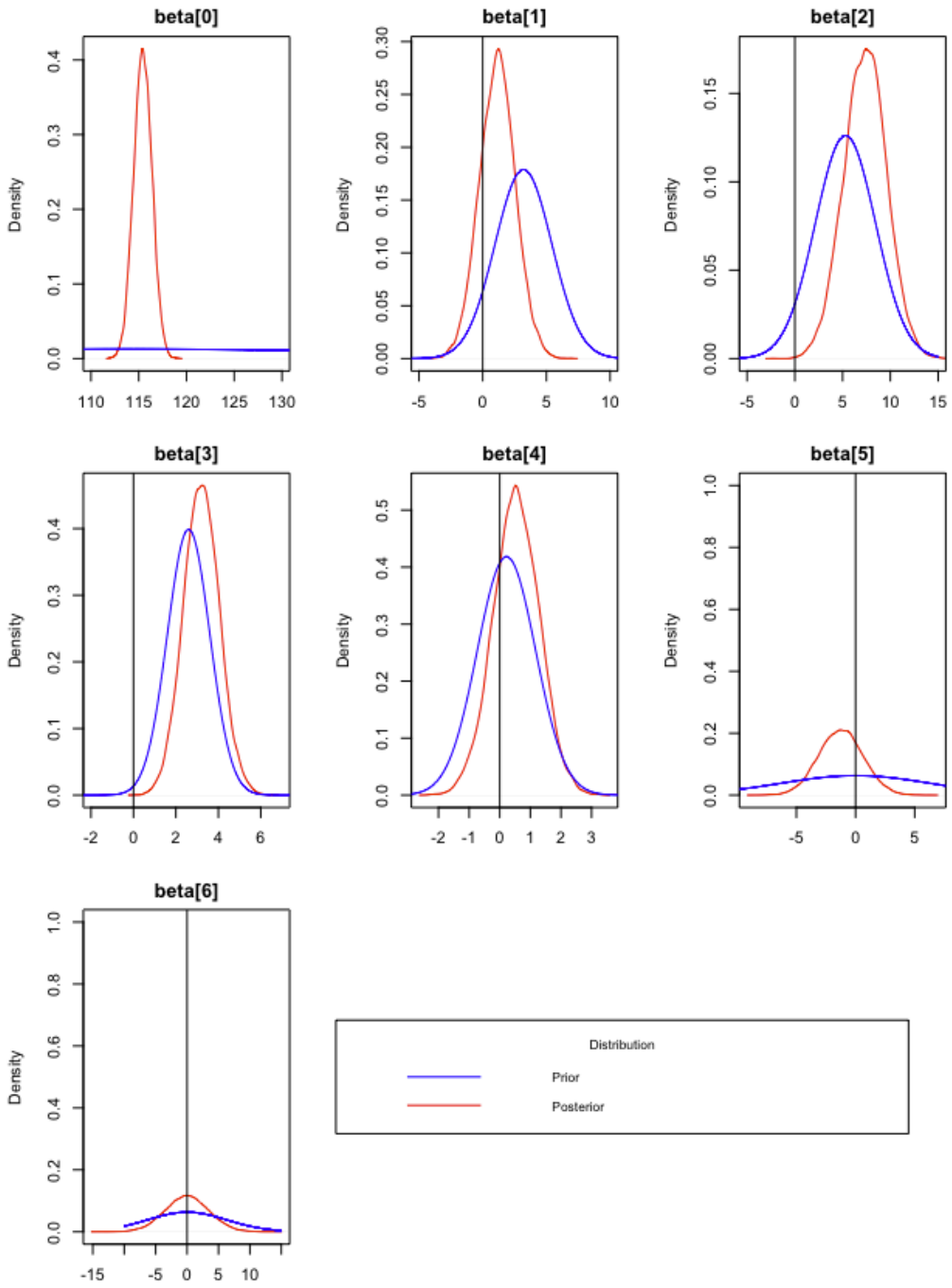

Figure 2. Prior and posterior densities of fixed effects (beta[0-6]). Prior densities are blue; posterior densities are red. Vertical black line in all plots except for the beta[0] (intercept) plot is at zero point.

Table 2. Sensitivity analysis for fixed effect priors. Posterior means, standard deviations, and probabilities for all fixed effects (Beta0-6) are recorded for low, medium, and high values of prior variance. Low variances are defined as those of the primary analysis divided by 3; high variances are defined as those of the primary analysis multiplied by 3. Medium variances matches that of primary analysis. Abbreviation: P = probability; SD = standard deviation.

Parameter	Variance	Mean	SD	P (< 0|Y)	P (> 0|Y)
Beta0	Low	115.54	0.84	0	1
	Medium	115.43	0.96	0	1
	High	115.17	1.12	0	1
Beta1	Low	1.88	1.03	0.03	0.97
	Medium	1.15	1.40	0.21	0.79
	High	0.72	1.67	0.34	0.66
Beta2	Low	6.45	1.53	0	1
	Medium	7.36	2.23	0	1
	High	8.53	2.84	0	1
Beta3	Low	2.88	0.54	0	1
	Medium	3.20	0.84	0	1
	High	3.68	1.17	0	1
Beta4	Low	0.36	0.51	0.24	0.76
	Medium	0.54	0.75	0.24	0.76
	High	0.74	0.99	0.23	0.77
Beta5	Low	-1.54	1.56	0.84	0.16
	Medium	-1.24	1.86	0.75	0.25
	High	-1.15	2.19	0.70	0.30
Beta6	Low	0.63	2.61	0.41	0.59
	Medium	-0.01	3.43	0.50	0.50
	High	-1.31	4.19	0.62	0.38

```
model
{
  for(i in 1:203) {
    for(j in 1:obscount[i]){
      s[i,j] <- cumcount[i] + j
          y[i,j] ~ dnorm( mu[i,j], tau.epsilon)
          mu[i,j] <- inprod(x[s[i,j],],beta[]) + gamma[i]
    }
    gamma[i] ~ dnorm(0, tau.gamma)
  }
  for(k in 1:7) {
        beta[k] ~ dnorm( m[k], prec[k] )
  }
  tau.gamma ~ dgamma(da,db)
  tau.epsilon ~ dgamma(ta,tb)
  sigma <- 1/sqrt(tau.epsilon)
  sqrtd <- 1/sqrt(tau.gamma)
}
```

Figure 3. Main BUGS model.

```
# Declare all vectors, matrices, and priors
bpdata = list(y = final, cumcount = cumcount,
  x = matrix(
    data=c(rep(1,9573), nursebp_final[,3], nursebp_final[,4], nursebp_final[,5],
      nursebp_final[,6], nursebp_final[,7], nursebp_final[,8]),
    byrow=F, ncol=7),
  obscount = nursebp_count_vector, da=61, db = 5184, ta=237.25, tb= 14066.525,
  m=c(114.0,3.2, 5.3, 2.6, 0.22, 0, 0), prec = c(
    0.001,0.20,0.1, 1, 1.1, 0.025, 0.025))

# Initial values and parameters
bpinits = rep(list(list( beta = c(117.0,0,0,0,0,0,0),
  gamma=as.vector(rnorm(203, mean = 0, sd = 7)), tau.gamma=1,
  tau.epsilon = 1)), 5)

bpparameters = c("beta","tau.epsilon", "tau.gamma", "sqrtd", "sigma")

# Run the model
run1 = jags(bpdata, bpinits, bpparameters,
               "bloodpressure.txt", n.chains=5, n.iter=5000,
               n.burnin=1000, n.thin=1)
```

Figure 4. Code that defines data, initial values, and parameters of the primary analysis as well as the *jags* function used to run the model.