POLI 5003: Problem Set # 3 - Team D's Answers (Corrected Version from 3-13-14 Class)

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The Partido Revolucionario Institucional (PRI) maintained authoritarian rule over Mexico for more than seventy years, from the end of the Mexican Revolution until after the July 2000 elections. The dataset accompanying this assignment (mex2000.dta) is drawn from a survey conducted during that electoral campaign. You will use it to examine the predictors of Mexicans' attitudes towards the PRI and its opponents at that critical time in the country's history.

```
> # Setup
> require(foreign)
> mex <- read.dta("mex2000.dta")</pre>
> var.labels <- attr(mex, "var.labels")</pre>
> data.key <- data.frame(var.name=names(mex),var.labels)</pre>
> data.key
    var.name
1
     PRIfeel
2
     PANfeel
3
     PRDfeel
4
     prefPRI
5
     prefPAN
6
    rightide
7
    econpers
8
     econnat
9
     corrupt
10
       crime
      female
11
12
         ses
13 churchatt
                                                                             var.labels
                            What is your opinion of the PRI? O=very bad 10=very good
1
2
                            What is your opinion of the PAN? O=very bad 10=very good
                            What is your opinion of the PRD? O=very bad 10=very good
3
                  PRIfeel - feeling toward best-liked opposition party (PAN or PRD)
4
5
                                                                     PANfeel - PRIfeel
6
                                      Political ideology, 0=very left, 10=very right
7
   Change in personal economic situation, 1 yr. 1=much worse now, 5=much better now
   View of national economic sit. over past yr. 1=much worse now, 5=much better now
8
9
                View of gov't corruption, past yr. 1=much less now, 5=much more now
```

```
View of crime over past year, 1=much less now, 5=much more now
Female? 0=no, 1=yes
Socioeconomic status, 1=very low, 6=very high
Church attendance: 1=never, 2=occationally, 3=monthly, 4=weekly, 5=more often
```

1. During its long rule, the PRI worked to present itself as the party of all Mexicans and was therefore something of an ideological chameleon. Nevertheless, we might hypothesize that people who leaned more to the right would hold more favorable views of this authoritarian party (Americanists may recall V.O. Key's writings about the one-party South), and suppose we want to control for their assessments of the recent performance of the national economy as well as of their personal characteristics. Is this ideology hypothesis supported by a regression of PRIfeel using Empirical Bayes and the other default settings of MCMCpack? How do you know? Describe the estimated effect of ideology on attitudes toward the PRI.

1. Empirical mean and standard deviation for each variable, plus standard error of the mean:

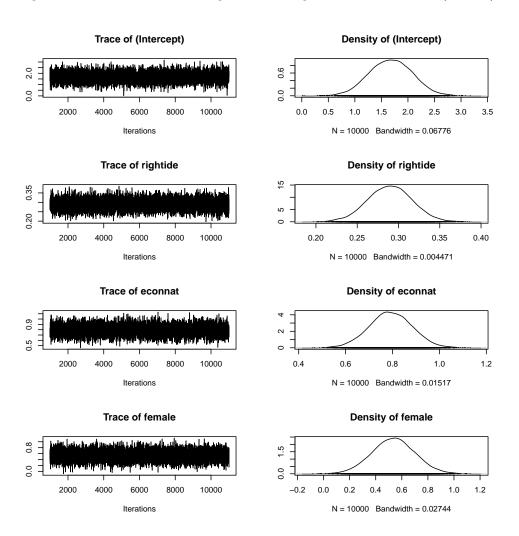
```
SD Naive SE Time-series SE
                Mean
(Intercept)
             1.67619 0.40335 0.0040335
                                             0.0040335
rightide
             0.28958 0.02661 0.0002661
                                             0.0002661
econnat
             0.79223 0.09095 0.0009095
                                             0.0009095
female
             0.53576 0.16416 0.0016416
                                             0.0016416
            -0.24019 0.07312 0.0007312
                                             0.0007312
ses
             0.03911 0.07177 0.0007177
churchatt
                                             0.0007177
sigma2
            10.39071 0.36604 0.0036604
                                             0.0036604
```

2. Quantiles for each variable:

	2.5%	25%	50%	75%	97.5%
(Intercept)	0.8983	1.398769	1.67847	1.95341	2.45652
rightide	0.2373	0.271463	0.28965	0.30738	0.34194
econnat	0.6126	0.731997	0.79129	0.85297	0.97056
female	0.2154	0.426275	0.53633	0.64518	0.86227
ses	-0.3865	-0.288992	-0.23960	-0.19139	-0.09923
churchatt	-0.1023	-0.008479	0.03875	0.08661	0.17974
sigma2	9.6938	10.142519	10.38043	10.63283	11.13311

Based on the results, the coefficient for rightide, representing the political ideology of the survey respondents, is 0.2896. This means that for every one unit increase in political ideology (i.e. as respondents consider themselves more conservative), respondents' feelings towards the PRI will increas by 0.2896 units. In regards to whether this estimated effect is statistically significant, the 95% high density interval (HDI) for rightide is (0.2373, 0.3419). In other words, the probability that the true posterior parameter value, $\beta_{rightide}$, is between 0.2373 and 0.3419 is 95%. Because the 95% HDI for rightide does not include 0, there is sufficient to evidence supporting the hypothesis that repsondents who lean towards the right, ideologically, will have higher feelings for the PRI.

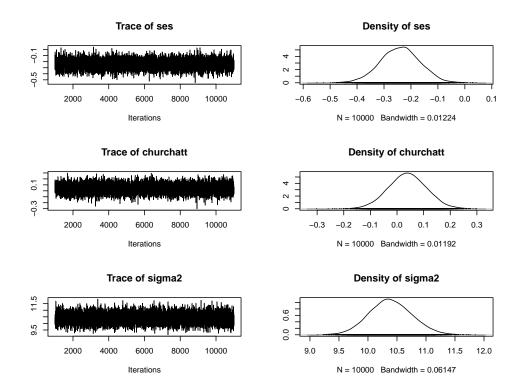
Figure 1: Diadnostic Checking for Convergence for Model #1 (Part 1)



2. Suppose the literature further suggests that the effect of ideology on respondents' feelings about the PRI would be weaker among those who held more positive assessments of the national economy's recent performance. Assess this conditional hypothesis using Empirical Bayes and the other default settings of MCMCpack.

```
> m2.mcmc <- MCMCregress(PRIfeel ~ rightide + econnat + female
+ ses + churchatt + rightide:econnat,data=mex)
> summary(m2.mcmc)
Iterations = 1001:11000
Thinning interval = 1
```

Figure 2: Diadnostic Checking for Convergence for Model #1 (Part 2)



Number of chains = 1 Sample size per chain = 10000

1. Empirical mean and standard deviation for each variable, plus standard error of the mean:

	Mean	SD	Naive SE	Time-series SE
(Intercept)	1.41147	0.62630	0.0062630	0.0062630
rightide	0.33257	0.08279	0.0008279	0.0008279
econnat	0.89110	0.20038	0.0020038	0.0020038
female	0.53736	0.16323	0.0016323	0.0015819
ses	-0.24062	0.07281	0.0007281	0.0007281

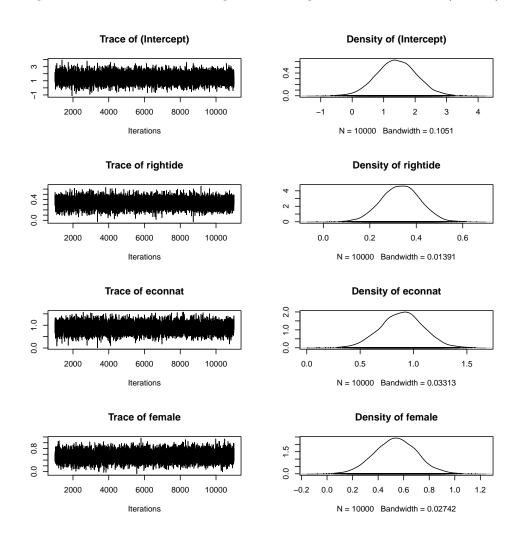
churchatt	0.04003	0.07218	0.0007218	0.0007139
rightide:econnat	-0.01579	0.02866	0.0002866	0.0002866
sigma2	10.39458	0.36422	0.0036422	0.0036422

2. Quantiles for each variable:

	2.5%	25%	50%	75%	97.5%
(Intercept)	0.20047	0.992144	1.40466	1.830227	2.66340
rightide	0.17200	0.276079	0.33324	0.388833	0.49219
econnat	0.49765	0.758791	0.89492	1.023063	1.27942
female	0.21557	0.426987	0.53839	0.648121	0.86345
ses	-0.38398	-0.290135	-0.24085	-0.191804	-0.09845
churchatt	-0.09990	-0.009025	0.04089	0.088459	0.17973
rightide:econnat	-0.07145	-0.034925	-0.01589	0.003381	0.04047
sigma2	9.70193	10.141389	10.38804	10.636205	11.12725

According to the results, as econnat increases one unit, the effect respondents' political ideology has on their feelings towards the PRI decreases by 0.0158 units, from a base level effect of 0.3326 units. In other words, if econnat= 0, then as rightide increased one unit, respondents' feelings towards the PRI would increase by 0.3326 units. As econnat increases one unit, however, the effect political ideology has on respondents' feelings toward the PRI is now 0.3326 - [0.0158(econnat)]. Although the coefficient of the interaction term is in the right direction, its 95% HDI includes the value 0. Therefore, we are unable to fully support the conditional hypothesis. In other words, there is the possibility that the effect of ideology on respondents' feelings about the PRI may not be statistically significantly weaker among those who held more positive assessments of the national economy's recent performance.

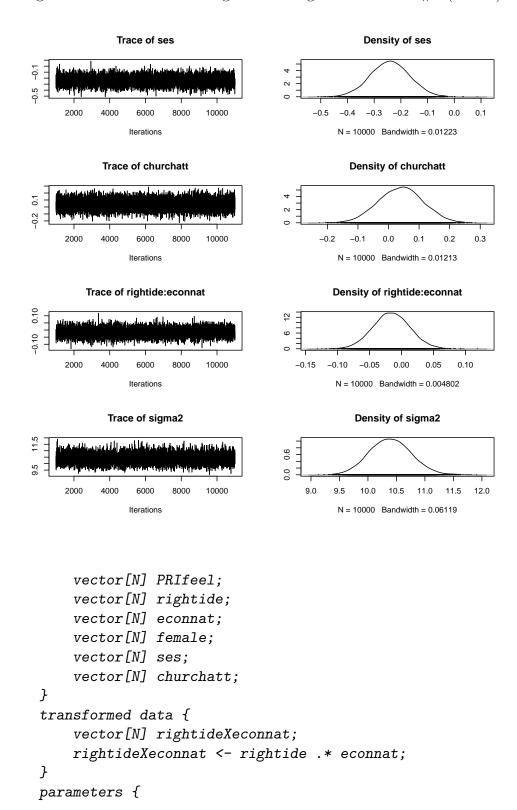
Figure 3: Diadnostic Checking for Convergence for Model #2 (Part 1)



3. Suppose a "helpful" reviewer points out that Empirical Bayes imposes a very strong set of priors, and that noninformative priors may yield a different result. Going well beyond the call of duty, this reviewer even offers some code for you to study and then try out. Is the reviewer correct that your conclusions regarding the conditional hypothesis change with a different prior?

```
> require(rstan)
> # First we have to define the model
> PRIfeel.code <- '
+     data {
+     int<lower=0> N;
```

Figure 4: Diadnostic Checking for Convergence for Model #2 (Part 2)



```
// coef for constant (default prior is uniform,
          real beta1;
          real beta2;
          real beta3;
          real beta4;
          real beta5;
          real beta6;
          real beta7;
          real<lower=0> sigma;
      }
      model {
          PRIfeel ~ normal(beta1 + beta2 * rightide + beta3 * econnat +
                                beta4 * female + beta5 * ses +
                                beta6 * churchatt + beta7 * rightideXeconnat, sigma
      }
> # Then put the data into the expected format
> mex.data <- list(N = nrow(mex), PRIfeel = mex$PRIfeel, rightide = mex$rightide,
                     econnat = mex$econnat, female = mex$female,
                     ses = mex$ses, churchatt = mex$churchatt)
> # Now we can run it
> set.seed(324)
> m1.stan <- stan(model_code = PRIfeel.code, data = mex.data,</pre>
                  iter = 1000, chains = 3)
TRANSLATING MODEL 'PRIfeel.code' FROM Stan CODE TO C++ CODE NOW.
COMPILING THE C++ CODE FOR MODEL 'PRIfeel.code' NOW.
      2 [main] make 49764 find_fast_cwd: WARNING: Couldn't compute FAST_CWD pointer
the public mailing list cygwin@cygwin.com
cygwin warning:
 MS-DOS style path detected: C:/PROGRA~1/R/R-3.0.3/etc/x64/Makeconf
 Preferred POSIX equivalent is: /cygdrive/c/PROGRA~1/R/R-3.0.3/etc/x64/Makeconf
 CYGWIN environment variable option "nodosfilewarning" turns off this warning.
 Consult the user's guide for more details about POSIX paths:
    http://cygwin.com/cygwin-ug-net/using.html#using-pathnames
C:/Users/Desmond/Documents/R/win-library/3.0/rstan/include//stansrc/stan/agrad/rev/
C:/Users/Desmond/Documents/R/win-library/3.0/rstan/include//stansrc/stan/agrad/rev/
SAMPLING FOR MODEL 'PRIfeel.code' NOW (CHAIN 1).
             1 / 1000 [ 0%]
Iteration:
                              (Warmup)
Iteration: 100 / 1000 [ 10%] (Warmup)
Iteration: 200 / 1000 [ 20%]
                              (Warmup)
Iteration: 300 / 1000 [ 30%]
                            (Warmup)
```

Iteration: 400 / 1000 [40%] (Warmup)

```
Iteration: 500 / 1000 [ 50%]
                               (Warmup)
Iteration: 600 / 1000 [ 60%]
                               (Sampling)
Iteration: 700 / 1000 [ 70%]
                               (Sampling)
Iteration: 800 / 1000 [ 80%]
                               (Sampling)
Iteration: 900 / 1000 [ 90%]
                               (Sampling)
Iteration: 1000 / 1000 [100%]
                                (Sampling)
Elapsed Time: 55.842 seconds (Warm-up)
              44.843 seconds (Sampling)
              100.685 seconds (Total)
SAMPLING FOR MODEL 'PRIfeel.code' NOW (CHAIN 2).
Iteration:
             1 / 1000 [ 0%]
                               (Warmup)
Iteration: 100 / 1000 [ 10%]
                               (Warmup)
Iteration: 200 / 1000 [ 20%]
                               (Warmup)
Iteration: 300 / 1000 [ 30%]
                               (Warmup)
Iteration: 400 / 1000 [ 40%]
                               (Warmup)
Iteration: 500 / 1000 [ 50%]
                               (Warmup)
Iteration: 600 / 1000 [ 60%]
                               (Sampling)
Iteration: 700 / 1000 [ 70%]
                               (Sampling)
Iteration: 800 / 1000 [ 80%]
                               (Sampling)
Iteration: 900 / 1000 [ 90%]
                               (Sampling)
Iteration: 1000 / 1000 [100%]
                                (Sampling)
Elapsed Time: 49.936 seconds (Warm-up)
              40.292 seconds (Sampling)
              90.228 seconds (Total)
SAMPLING FOR MODEL 'PRIfeel.code' NOW (CHAIN 3).
Iteration:
             1 / 1000 [ 0%]
                               (Warmup)
Iteration: 100 / 1000 [ 10%]
                               (Warmup)
Iteration: 200 / 1000 [ 20%]
                               (Warmup)
Iteration: 300 / 1000 [ 30%]
                               (Warmup)
Iteration: 400 / 1000 [ 40%]
                               (Warmup)
Iteration: 500 / 1000 [ 50%]
                               (Warmup)
Iteration: 600 / 1000 [ 60%]
                               (Sampling)
Iteration: 700 / 1000 [ 70%]
                               (Sampling)
Iteration: 800 / 1000 [ 80%]
                               (Sampling)
Iteration: 900 / 1000 [ 90%]
                               (Sampling)
Iteration: 1000 / 1000 [100%]
                                (Sampling)
Elapsed Time: 57.939 seconds (Warm-up)
              41.374 seconds (Sampling)
```

99.313 seconds (Total)

> print(m1.stan)

Inference for Stan model: PRIfeel.code.
3 chains, each with iter=1000; warmup=500; thin=1;
post-warmup draws per chain=500, total post-warmup draws=1500.

	mean	se_mean	sd	2.5%	25%	50%	75%	97.5%	n_eff	Rhat
beta1	1.5	0.0	0.6	0.3	1.0	1.4	1.9	2.7	472	1
beta2	0.3	0.0	0.1	0.2	0.3	0.3	0.4	0.5	522	1
beta3	0.9	0.0	0.2	0.5	0.7	0.9	1.0	1.3	552	1
beta4	0.5	0.0	0.2	0.2	0.4	0.5	0.6	0.8	1143	1
beta5	-0.2	0.0	0.1	-0.4	-0.3	-0.2	-0.2	-0.1	924	1
beta6	0.0	0.0	0.1	-0.1	0.0	0.0	0.1	0.2	968	1
beta7	0.0	0.0	0.0	-0.1	0.0	0.0	0.0	0.0	523	1
sigma	3.2	0.0	0.1	3.1	3.2	3.2	3.3	3.3	1155	1
lp	-2713.0	0.1	2.0	-2717.6	-2714.1	-2712.7	-2711.6	-2710.2	562	1

Samples were drawn using NUTS(diag_e) at Thu Mar 13 12:11:59 2014. For each parameter, n_eff is a crude measure of effective sample size, and Rhat is the potential scale reduction factor on split chains (at convergence, Rhat=1).

```
> m1.stan.sim <- as.data.frame(m1.stan)</pre>
> HDI.posterior <- function(data = NULL, mass = .95) {
      n.vars \leftarrow dim(data)[2]-2
      results.HDI <- matrix(rep(NA, 3*n.vars), nrow=n.vars, ncol=3)
      for (var in 1:n.vars) {
           post <- data[,var]</pre>
           sorted.post <- sort(post)</pre>
           ci.idx <- floor(mass * length(sorted.post))</pre>
           n.ci <- length(sorted.post) - ci.idx</pre>
           ci.width <- rep(0, n.ci)</pre>
           for (i in 1:n.ci) {
                ci.width[i] <- sorted.post[i+ci.idx] - sorted.post[i]</pre>
           HDI.min <- sorted.post[which.min(ci.width)]</pre>
           HDI.max <- sorted.post[which.min(ci.width)+ci.idx]</pre>
           mean.post <- mean(post)</pre>
           results.HDI[var,] <- c(mean.post, HDI.min, HDI.max)</pre>
      results.HDI <- as.data.frame(results.HDI)</pre>
```

```
names(results.HDI) \leftarrow c("b", "lb", "ub")
+
      return(results.HDI)
+ }
> HDI.posterior(data=m1.stan.sim)
            b
                        1b
                                    ub
   1.45680481
               0.20047082
                           2.65509789
1
2
  0.32983824 0.16562228
                           0.49026322
  0.88123471 0.49915704
                            1.28159359
  0.52589903 0.20198199
                           0.83908045
5 -0.24496189 -0.38062972 -0.10160730
  0.04090839 -0.09469561
                            0.19153111
7 -0.01489438 -0.07351261
                            0.04247551
```

While we appreciate the time and effort the reviewer put into providing us with this code, unfortunately the results above do not reveal any siginificant differences between the "Empirical Bayes" model and the "Noninformative Priors" model. As the results above demonstrate, the estimated value of beta #2, representing the coefficient for political ideology is 0.3298. The coefficient value for political ideology from the "Empirical Bayes" model is 0.3326, resulting in 0.0028 difference between the two coefficients. Similar differences are revelaed for the other variables in the model. Thus, it is with deep regret we must state that the reviewer is incorrect in stating that we will receive different results with a noninformative prior.

4. Assess the original, unconditional hypothesis using noninformative priors. Include a graph of the posterior distribution for the effect of ideology on feelings toward the PRI. Also graph the highest density intervals of the posteriors of the effects of all variables in the model, remembering to standardize the continuous variables by dividing them by twice their standard deviations.

```
real beta2;
                       real beta3;
                       real beta4;
                       real beta5;
                       real beta6;
                       real<lower=0> sigma;
              }
             model {
                       PRIfeel ~ normal(beta1 + beta2 * rightide + beta3 * econnat +
                                                                        beta4 * female + beta5 * ses +
                                                                        beta6 * churchatt, sigma);
              }
> #Standardizing ``Continuous'' Variables
> mex2 <- mex
> for (iv in c(6,8,12,13)) {
                  mex2[,iv] \leftarrow mex2[,iv]/(2*sd(mex2[,iv]))
+ }
> # Then put the data into the expected format
> mex2.data <- list(N = nrow(mex2), PRIfeel = mex2$PRIfeel, rightide = mex2$right:
                                                 econnat = mex2$econnat, female = mex2$female,
                                                 ses = mex2$ses, churchatt = mex2$churchatt)
> # Now we can run it
> set.seed(3182)
> m2.stan <- stan(model_code = PRIfeel.code, data = mex2.data,
                                          iter = 1000, chains = 3)
TRANSLATING MODEL 'PRIfeel.code' FROM Stan CODE TO C++ CODE NOW.
COMPILING THE C++ CODE FOR MODEL 'PRIfeel.code' NOW.
              1 [main] make 46688 find_fast_cwd: WARNING: Couldn't compute FAST_CWD pointer
the public mailing list cygwin@cygwin.com
cygwin warning:
    MS-DOS style path detected: C:/PROGRA~1/R/R-3.0.3/etc/x64/Makeconf
    Preferred POSIX equivalent is: /cygdrive/c/PROGRA~1/R/R-3.0.3/etc/x64/Makeconf
    CYGWIN environment variable option "nodosfilewarning" turns off this warning.
    Consult the user's guide for more details about POSIX paths:
        http://cygwin.com/cygwin-ug-net/using.html#using-pathnames
C:/Users/Desmond/Documents/R/win-library/3.0/rstan/include//stansrc/stan/agrad/rev/
{\tt C:/Users/Desmond/Documents/R/win-library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stansrc/stan/agrad/rev/library/3.0/rstan/include//stan/agrad/rev/library/3.0/rstan/include//stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan/agrad/rev/library/stan
SAMPLING FOR MODEL 'PRIfeel.code' NOW (CHAIN 1).
Iteration:
                             1 / 1000 [ 0%]
                                                                     (Warmup)
```

Iteration: 100 / 1000 [10%] (Warmup)

```
(Warmup)
Iteration: 300 / 1000 [ 30%]
                               (Warmup)
Iteration: 400 / 1000 [ 40%]
                               (Warmup)
Iteration: 500 / 1000 [ 50%]
                               (Warmup)
Iteration: 600 / 1000 [ 60%]
                               (Sampling)
Iteration: 700 / 1000 [ 70%]
                               (Sampling)
Iteration: 800 / 1000 [ 80%]
                               (Sampling)
Iteration: 900 / 1000 [ 90%]
                               (Sampling)
Iteration: 1000 / 1000 [100%]
                                (Sampling)
Elapsed Time: 24.025 seconds (Warm-up)
              20.159 seconds (Sampling)
              44.184 seconds (Total)
SAMPLING FOR MODEL 'PRIfeel.code' NOW (CHAIN 2).
             1 / 1000 [ 0%]
Iteration:
                               (Warmup)
Iteration: 100 / 1000 [ 10%]
                               (Warmup)
Iteration: 200 / 1000 [ 20%]
                               (Warmup)
Iteration: 300 / 1000 [ 30%]
                               (Warmup)
Iteration: 400 / 1000 [ 40%]
                               (Warmup)
Iteration: 500 / 1000 [ 50%]
                               (Warmup)
Iteration: 600 / 1000 [ 60%]
                               (Sampling)
Iteration: 700 / 1000 [ 70%]
                               (Sampling)
Iteration: 800 / 1000 [ 80%]
                               (Sampling)
Iteration: 900 / 1000 [ 90%]
                               (Sampling)
Iteration: 1000 / 1000 [100%]
                                (Sampling)
Elapsed Time: 20.935 seconds (Warm-up)
              20.25 seconds (Sampling)
              41.185 seconds (Total)
SAMPLING FOR MODEL 'PRIfeel.code' NOW (CHAIN 3).
Iteration:
             1 / 1000 [ 0%]
                               (Warmup)
Iteration: 100 / 1000 [ 10%]
                               (Warmup)
Iteration: 200 / 1000 [ 20%]
                               (Warmup)
Iteration: 300 / 1000 [ 30%]
                               (Warmup)
Iteration: 400 / 1000 [ 40%]
                               (Warmup)
Iteration: 500 / 1000 [ 50%]
                               (Warmup)
Iteration: 600 / 1000 [ 60%]
                               (Sampling)
Iteration: 700 / 1000 [ 70%]
                               (Sampling)
Iteration: 800 / 1000 [ 80%]
                               (Sampling)
Iteration: 900 / 1000 [ 90%]
                               (Sampling)
```

Iteration: 200 / 1000 [20%]

> print(m2.stan)

Inference for Stan model: PRIfeel.code.
3 chains, each with iter=1000; warmup=500; thin=1;
post-warmup draws per chain=500, total post-warmup draws=1500.

	mean	se_mean	sd	2.5%	25%	50%	75%	97.5%	n_eff	Rhat
beta1	1.7	0.0	0.4	0.8	1.4	1.6	1.9	2.5	731	1
beta2	1.8	0.0	0.2	1.5	1.7	1.8	1.9	2.1	983	1
beta3	1.4	0.0	0.2	1.1	1.3	1.4	1.5	1.7	1166	1
beta4	0.5	0.0	0.2	0.2	0.4	0.5	0.6	0.8	1299	1
beta5	-0.5	0.0	0.2	-0.9	-0.6	-0.5	-0.4	-0.2	988	1
beta6	0.1	0.0	0.2	-0.2	0.0	0.1	0.2	0.4	1290	1
sigma	3.2	0.0	0.1	3.1	3.2	3.2	3.3	3.3	1500	1
lp	-2712.8	0.1	2.0	-2717.4	-2713.7	-2712.4	-2711.3	-2710.1	550	1

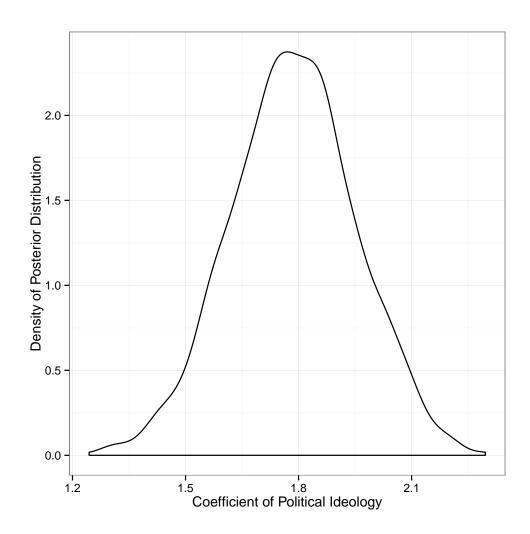
Samples were drawn using NUTS(diag_e) at Thu Mar 13 12:15:52 2014. For each parameter, n_eff is a crude measure of effective sample size, and Rhat is the potential scale reduction factor on split chains (at convergence, Rhat=1).

```
> m2.stan.sim <- as.data.frame(m2.stan)</pre>
> HDI.posterior <- function(data = NULL, mass = .95) {</pre>
      n.vars \leftarrow dim(data)[2]-2
       results.HDI <- matrix(rep(NA, 3*n.vars), nrow=n.vars, ncol=3)
      for (var in 1:n.vars) {
           post <- data[,var]</pre>
           sorted.post <- sort(post)</pre>
           ci.idx <- floor(mass * length(sorted.post))</pre>
           n.ci <- length(sorted.post) - ci.idx</pre>
           ci.width <- rep(0, n.ci)</pre>
           for (i in 1:n.ci) {
                ci.width[i] <- sorted.post[i+ci.idx] - sorted.post[i]</pre>
           HDI.min <- sorted.post[which.min(ci.width)]</pre>
           HDI.max <- sorted.post[which.min(ci.width)+ci.idx]</pre>
           mean.post <- mean(post)</pre>
           results.HDI[var,] <- c(mean.post, HDI.min, HDI.max)</pre>
```

```
}
      results.HDI <- as.data.frame(results.HDI)
      names(results.HDI) \leftarrow c("b", "lb", "ub")
      return(results.HDI)
+ }
> HDI.posterior(data=m2.stan.sim)
            b
                       1b
                                   ub
               0.8291510
1
   1.65009761
                           2.5249291
2
   1.78571488
               1.4744037
                           2.1199590
3
  1.41113192
               1.0760798
                           1.7088341
               0.2374128
  0.53423627
                           0.8388078
5 -0.52439728 -0.8334280 -0.1685682
  0.09311665 -0.2322872
                           0.4134149
```

Figure #5 displays the posterior distribution of the effect on ideology of the PRI. As Figure #5 demonstrates, the 95% HDI is (0.2306, 0.3356), while the 95% HDI for the same model, caclulated via "Empirical Bayes" is (0.2715, 0.3419); thus the "Noninformative Prior" model's HDI is wider by 0.0346 units. Figure #6, however, displays the estimates, and HDI's, for the independent variables. All included variables, except for chuirch attendence and Socio economic status have a positive effect on ideology. However, socioeconomic status has a negative effect on an individuals ideology towards the PRI and church attendance, because the 95% HDI contains 0, has no effect. Altogether, these two figures provide evidence in support of the hypothesis stated in question #1: respondents, whose ideology leans more towards the right, have a more favorable of the PRI.

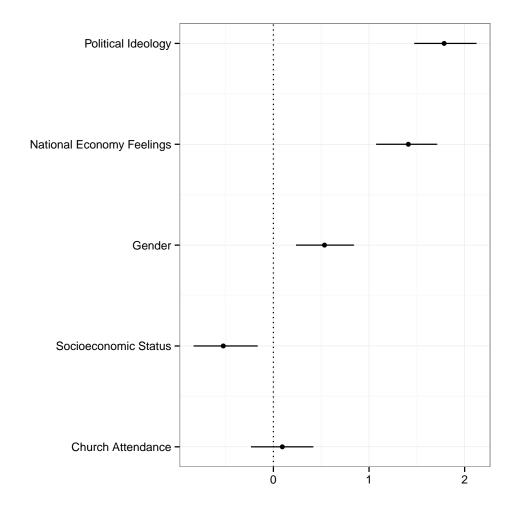
Figure 5: Posterior Distribution of the Effect of Ideology



References

Gelman, Andrew. 2008. "Scaling Regression Inputs by Dividing by Two Standard Deviations." *Statistics in Medicine* 27:2865–2873.

Figure 6: Posterior Distribution of the Effect of Ideology



Note: Continuous variables rescaled by dividing by twice their standard deviations per Gelman (2008).