BWF Badminton tournaments

Bayesian Data Analysis Project, 09-Dec-2018

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1 Introduction

Goal: analyze the distribution of outcomes in a badminton tournament.

Approach: apply Bayesian data analysis on historical data of badminton tournaments. The estimand of interest is the probability of a certain outcome. The modelling of a match outcome will be explained more in section 2.

Implementation:

- Start with some naive assumption of the estimand, in order to choose the model later
- Collect and preprocess data
- Decide on prior choices and models
- Do stan analysis on each models
- Model comparision (using PSIS-LOO)
- Do posterior predictive comparision between models
- Conclusion, possible improvements

2 Analysis problem

2.1 Discretizing the problem

In one tournament, there are 8 seed players and some unranked players. To discretize the ranking spread, we chose 12th as the rank for all unranked players. The spread is calculated as follows:

Spread (from 1st player perspective) = Rank(2nd player) - Rank(1st player)

E.g.

- Spread(from 1st rank player to 8th rank player) = 8 - 1 = 7
- Spread(from 2nd rank player to unrank player) = 12 - 2 = 10
- Spread(from unrank player to 3rd rank player) = 3 - 12 = -9

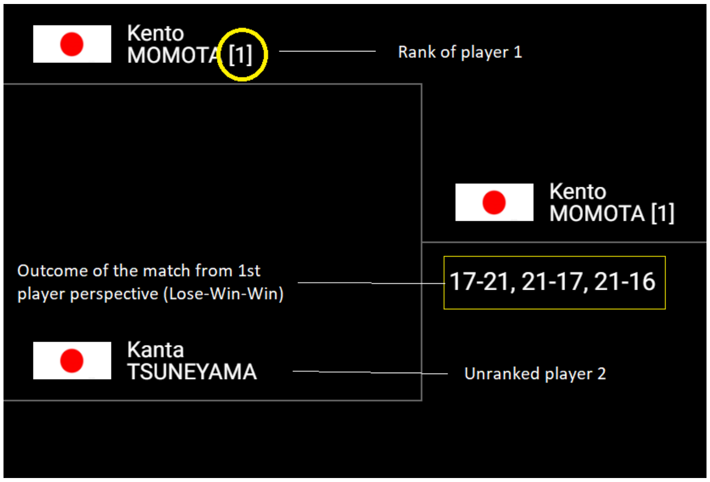
The discrete space for ranking spread is then **[-11,-10,-9,...,9,10,11]**

A match (which has at most 3 games) has 6 possible outcomes:

1. Lose Lose -> Lose
2. Lose Win Lose -> Lose
3. Win Lose Lose -> Lose
4. Lose Win Win -> Win
5. Win Lose Win -> Win
6. Win Win -> Win

To discretize this parameter, we map the outcome of a match to **[1,2,3,4,5,6]** in terms of win degree (i.e. win degree 1 is the worst, and win degree 6 is the best).

For the match below, ranking spread is 11, win degree is 4



2.2 Modeling the problem

Unless stated otherwise, all information in the data are from 1st player perspective
An observation of a match includes 2 pieces of information:

- ranking spread
- win degree

To formulate the observations as a one dimensional space collection, we need to reduce the matrix 23x6 (23 different spreads, 6 different win degrees) of all possible raw observations. The intuition of the reduction is as follows:

- With the same ranking spread, higher win degree correlates to higher value (see arrow A in image below)
- With the same win degree, lower ranking spread correlates to higher value (see arrow B in image below)
- Step between value is 1

With the given constraint, we will have **28 possible values of observation from [1,28].** The mapping is as follow (columns are win degrees and rows are ranking spreads)

		A					
		6	5	4	3	2	1
	-11	28	27	26	25	24	23
	-10	27	26	25	24	23	22
	-9	26	25	24	23	22	21
	-8	25	24	23	22	21	20
B	⋮	.	.	.	.	.	.
	⋮	.	.	.	.	.	.
	8	9	8	7	6	5	4
	9	8	7	6	5	4	3
	10	7	6	5	4	3	2
	11	6	5	4	3	2	1

2.3 Analysing the problem

The problem analysis explores the distribution of the observations, especially concentrating on the predictive distribution of the new tournament. Furthermore, we will try to analyze the affect of the different models and prior choices.

3 Dataset and data model

The dataset is collected from Badminton World Federation (BWF) tournament database using Scrapy crawler. After collecting, the data is preprocessed as stated in the previous section. In the end, the format of data is similar to the factory data assignments. A peek of the data:

In [3]:
```
show_first_rows_of_data()
```

Out[3]:

	Tournament 1	Tournament 2	Tournament 3	Tournament 4	Tournament 5
Match 1	6.0	17.0	16.0	6.0	1.0
Match 2	15.0	15.0	17.0	13.0	17.0
Match 3	16.0	7.0	4.0	17.0	5.0
Match 4	15.0	13.0	17.0	17.0	13.0
Match 5	19.0	20.0	20.0	15.0	17.0

In [4]:
```
show_summary_of_data()
```

Out[4]:

	Tournament 1	Tournament 2	Tournament 3	Tournament 4	Tournament 5
count	67.000000	67.000000	67.000000	67.000000	67.000000
mean	13.776119	14.388060	13.746269	14.880597	14.164179
std	5.746727	5.635266	5.329572	5.878885	5.703792
min	4.000000	3.000000	4.000000	3.000000	1.000000
25%	9.000000	10.000000	8.000000	10.000000	10.000000
50%	15.000000	15.000000	15.000000	16.000000	16.000000
75%	17.000000	18.000000	17.000000	17.000000	17.000000
max	25.000000	27.000000	26.000000	27.000000	27.000000

4 Prior choices

We decided to use two different priors:

- **Inverse gamma** is chosen on variance because it is the conjugate prior to normal likelihood and it has a closed form solution for the outcome of the posterior
- **Uniform** is chosen as weak prior to observe how sensitive is outcome in regards the prior and the data input

5 Model

In normal distribution where μ is known and σ^2 is unknown, the marginal posterior distribution $p(\sigma^2|y)$ can be computed as described below. The posterior distribution is computed using two different priors, whereas the first is an uniformative (uniform) and the second an informative (inverse gamma) prior.

Priors:

Uniform prior

$$p(\sigma^2) \propto Uniform(0, \infty)$$

Inverse gamma prior

$$p(\sigma^2) \propto (\sigma^2)^{-(a+1)} e^{-\beta/\sigma^2} \propto Inv - Gamma(\alpha, \beta)$$

where $\alpha = 1$ and $\beta = 1$ are the shape and scale parameters. Our prior assumption is that variance will be relatively small but we are not sure how small it is, and our guess is around [1,2]. The pdf of inverse gamma with $\alpha = 1$ and $\beta = 1$ is a good fit for our assumption.

Likelihood:

$$p(y|\mu, \sigma^2) \propto \prod_{i=1}^{N} p(y_i|\mu, \sigma^2) \propto N(y|\mu, \sigma^2)$$

where μ is known.

Posterior:

$$p(\sigma^2|y) \propto p(\sigma^2)p(y|\mu, \sigma^2)$$

Since one of the objective is to predict the distribution of a new tournament, we will use pooled and hierarchical model. The separate model is excluded because it handles the tournaments uniquely without having any common parameters which could be used to predict the new tournament.

In the pooled model the mean and the variance is computed from the combined data of all the tournaments and there is no distinction between different tournaments. This means that also the new tournament will have similar distibution as the predictive distribution of the tournaments.

In the hierarchical model each tournament is handled separately having own mean and common standard deviation. Furthermore, all the means are controlled by common hyperparameters (μ_0 and σ_0^2) which means that the means are drawn from the common distribution described by these hyperparameters. The result of the new tournament can be predicted using the common hyperparameters: first draw the mean from the common distribution and use it to sample the predictive distribution.

Then based on the prior choices, we have 4 different models:

- pooled with uniform prior
- pooled with inverse gamma prior for variance
- hierarchical with uniform prior
- hierarchical with inverse gamma prior for variance

6 Stan analysis of the models

For each model, we will show the Stan model and convergence diagnostic.

The Stan model is fitted using Stan's default parameters (4 chains, 1000 warmup iterations, 1000 sampling iteration, ending up to 4000 samples and 10 as maximum tree depth). In addition, to avoid false positive conclusion about divergences, the *adapt_delta* value is set to 0.9. This means that the fitting uses larger target acceptance probability and therefore all the divergences can be seen. If the resulting value is still 0 after this, we can verify that there are no divergences. If not, the divergences could be further analyzed by increasing *adapt_delta*.

Besides divergences, the convergence diagnostic includes a short discussion about $\hat{R}$ and n_eff. Generally, if the $\hat{R}$ values of the parameters are close to 1 and below 1.1, the fit has been good. The low $\hat{R}$ values combined with high effective sample size (n_eff) per transition informs that the Markov chains were mixed well. Note that discussion about depth tree and energy Bayesian fraction of missing information (E-BFMI) is left out because their results were same for all the models (depth tree 0 and E-BFMI did not give any information).

6.1 Pooled model with uniform prior

Stan model

The stan code of the model:

```
data {
  int<lower=0> N;       // Number of observations
  vector[N] y;           // N observations for J tournaments
}
parameters {
  real mu;              // Common mean
  real<lower=0> sigma;  // Common std
}
model {
  y ~ normal(mu, sigma);// Model for fitting data using tournament specific mu and common std
}
generated quantities {
  vector[N] log_lik;
  real ypred;

  ypred = normal_rng(mu, sigma);                  //Prediction of tournament
  for (n in 1:N)
    log_lik[n] = normal_lpdf(y[n] | mu, sigma);   //Log-likelihood
}
```

Convergence diagnostic

After compiling the model and fitting the combined data of the tournaments, the diagnostic of the fit was examined:

Diagnostic	Result
All $\hat{R}$ values close to 1	OK
Low $\hat{R}$ values combined with high effective sample size (n_eff)	OK
Divergences is 0	OK

All the results for pooled uniform prior model fitting are good. The full fit can be found in the *Attachment 1* and a shorter summary is shown below.

In [5]:
```
# Fit pooled uniform model
pool_uni_df, pool_uni_fit = compute_model(r'stan_code/pool_uniform_prior.stan', pooled_d
ata_model)
# Print summary of the fit
print_compact_fit(pool_uni_df)
```

```
Using cached StanModel
```

Out[5]:

	mean	se_mean	sd	2.5%	25%	50%	75%	97.5%	n_eff	Rhat
mu	14.1935	0.00603298	0.314179	13.5613	13.9842	14.2001	14.409	14.8204	2712	1.0010
sigma	5.66282	0.00441324	0.224035	5.24378	5.50642	5.65253	5.80839	6.12739	2577	1.0001
log_lik[0]	-3.70522	0.00177279	0.091105	-3.89356	-3.76527	-3.70164	-3.64204	-3.53086	2641	1.0007
log_lik[1]	-2.66381	0.000781838	0.0394576	-2.7439	-2.68967	-2.66273	-2.63632	-2.58826	2547	1.0002
log_lik[2]	-2.70475	0.000794411	0.0395853	-2.78604	-2.73049	-2.70434	-2.67761	-2.62968	2483	1.0003
...	...	...	...	...	...	...	...	...	...	..
log_lik[332]	-2.70475	0.000794411	0.0395853	-2.78604	-2.73049	-2.70434	-2.67761	-2.62968	2483	1.0003
log_lik[333]	-2.81336	0.000768998	0.0414903	-2.89455	-2.84142	-2.81289	-2.78428	-2.73293	2911	1.00091
log_lik[334]	-3.46419	0.001425	0.0745643	-3.61728	-3.51306	-3.46244	-3.41316	-3.32091	2738	1.0009
ypred	14.2868	0.0901683	5.70274	3.42566	10.3648	14.2842	18.1957	25.5974	4000	0.99999
lp__	-746.025	0.0248809	1.00668	-748.748	-746.425	-745.714	-745.295	-745.018	1637	0.99956

In [6]:
```
# Print additional checking of the fit
print_compact_fit_checking(pool_uni_fit, pool_uni_df)
```

```
Maximum value of the Rhat:
1.0012218111524749

Divergences:
0.0 of 4000 iterations ended with a divergence (0.0%)
```

6.2 Pooled model with inverse gamma prior

Stan model

The stan code of the model:

```
data {
  int<lower=0> N;        // Number of observations
  vector[N] y;            // N observations for J tournaments
  real<lower=0.1> alpha;  //Shape
  real<lower=0.1> beta;  //Scale
}
parameters {
  real mu;               // Common mean
  real<lower=0> sigmaSq; // Common var
}
transformed parameters {
  real<lower=0> sigma;
  sigma <- sqrt(sigmaSq);
}
model {
  sigmaSq ~ inv_gamma(alpha,beta);  // Prior
  y ~ normal(mu, sigma);            // Fitting of the model
}
generated quantities {
  vector[N] log_lik;
  real ypred;

  ypred = normal_rng(mu, sigma);    // Prediction of tournament
  for (n in 1:N)
    log_lik[n] = normal_lpdf(y[n] | mu, sigma); //Log-likelihood
}
```

Convergence diagnostic

The same procedure is followed here (as in the previous section) and similar results were obtained:

Diagnostic	Result
All $\hat{R}$ values close to 1	OK
Low $\hat{R}$ values combined with high effective sample size (n_eff)	OK
Divergences is 0	OK

All the results for pooled inverse gamma prior model fitting are good. The full fit can be found in the *Attachment 2* and a shorter summary is shown below.

In [7]:
```
# Fit pooled inverse gamma model
pool_inv_df, pool_inv_fit = compute_model(r'stan_code/pool_inverse_gamma_prior.stan', po
oled_data_model)
# Print summary of the fit
print_compact_fit(pool_inv_df)
```

```
Using cached StanModel
```

Out[7]:

	mean	se_mean	sd	2.5%	25%	50%	75%	97.5%	n_eff	Rhat
mu	14.1912	0.00659562	0.311324	13.5848	13.9808	14.1944	14.3957	14.8102	2228	1.00237
sigmaSq	31.819	0.0465451	2.42705	27.4953	30.0994	31.688	33.3725	36.8217	2719	1.00037
sigma	5.63676	0.0040921	0.21424	5.2436	5.48629	5.62921	5.77689	6.06809	2741	1.00037
log_lik[0]	-3.70983	0.00189007	0.0933245	-3.89964	-3.77044	-3.7058	-3.64535	-3.53664	2438	1.00087
log_lik[1]	-2.65936	0.000735954	0.0384743	-2.73647	-2.68499	-2.65882	-2.63316	-2.58596	2733	0.999909
...	...	...	...	...	...	...	...	...	...	..
log_lik[332]	-2.70068	0.000759725	0.039352	-2.78049	-2.72698	-2.70021	-2.67379	-2.62523	2683	0.999668
log_lik[333]	-2.81015	0.000869736	0.0394174	-2.88917	-2.83559	-2.80985	-2.78294	-2.7354	2054	1.00321
log_lik[334]	-3.46668	0.0015697	0.0761101	-3.62117	-3.51465	-3.46372	-3.41446	-3.3255	2351	1.00139
ypred	14.2633	0.08992	5.61407	3.23815	10.4847	14.328	18.0029	25.224	3898	0.999202
lp__	-751.202	0.0262385	1.01486	-753.917	-751.573	-750.898	-750.491	-750.235	1496	1.00201

In [8]:
```
# Print additional checking of the fit
print_compact_fit_checking(pool_inv_fit, pool_inv_df)
```

```
Maximum value of the Rhat:
1.00330613987631

Divergences:
0.0 of 4000 iterations ended with a divergence (0.0%)
```

6.3 Hierarchical model with uniform prior

6.3.1 Unsuccessful fitting

Stan model

The stan code of the model:

```
data {
  int<lower=0> N;  // Number of observations
  int<lower=0> J;  // Number of tournaments
  matrix[N,J] y;  // N observations for J tournaments
}
parameters {
  real mu0;             // Common mu for each J tournament's mu
  real<lower=0> sigma0; // Common std for each J tournament's mu
  real<lower=0> sigma; // Common std between tournaments
  real mu_tilde[J];    // Tournament specific mu
}
model {
  for (j in 1:J)
    mu[j] ~ normal(mu0, sigma0);       // Model for computing tournament specific mu from comm
on mu0 and sigma0
  for (j in 1:J)
    y[:,j] ~ normal(mu[j], sigma);  // Model for fitting data using tournament specific mu and
 common std
}
generated quantities {
  matrix[N,J] log_lik;
  real ypred[J];
  real mu_new;
  real ypred_new;

  for (j in 1:J)
     ypred[j] = normal_rng(mu[j], sigma);   // Predictive distibutions of all the tournaments
  mu_new = normal_rng(mu0, sigma0);       // Next posterior distribution from commonly learned
 mu0 and sigma0
  ypred_new = normal_rng(mu_new, sigma);    // Next predictive distibutions of new tournament

  for (j in 1:J)
     for (n in 1:N)
        log_lik[n,j] = normal_lpdf(y[n,j] | mu[j], sigma); //Log-likelihood
}
```

Convergence diagnostic attempt 1

The same procedure is followed here (as in the previous section) with minor change. The data used for fitting is a matrix where columns are the tournaments and rows are the matches in the tournaments. The diagnostic results are:

Diagnostic	Result
All $\hat{R}$ values close to 1	**NO** *lp__* is 1.4
Low $\hat{R}$ values combined with high effective sample size (n_eff)	**NO**
Divergences is 0	**NO** 8% of the target posterior was not explored

Because none of the conditions were fulfilled, in the next step we will try to improve the results by reducing the accuracy of the simulations by increasing the value of the *adapt_delta* parameter.

The results of the attempt 1 can be seen below.

In [9]:
```
# Fit hierarchical uniform model
hier_uni_df, hier_uni_fit = compute_model(r'stan_code/hier_uniform_prior.stan', hierarch
ical_data_model)
# Print the summary of the fit
print_compact_fit(hier_uni_df)
```

```
Using cached StanModel
```

Out[9]:

	mean	se_mean	sd	2.5%	25%	50%	75%	97.5%	n_eff	Rhat
mu0	14.222	0.0306316	0.518028	13.2403	13.9695	14.264	14.4845	15.0738	286	1.0193
sigma0	0.560246	0.0731073	0.759754	0.034287	0.172624	0.381537	0.709618	2.13192	108	1.03272
mu[0]	14.1029	0.0484593	0.477268	13.0482	13.8036	14.1453	14.4149	14.938	97	1.03988
mu[1]	14.2979	0.0144251	0.458663	13.3891	14.0025	14.3344	14.5531	15.27	1011	1.0106
mu[2]	14.0964	0.0545487	0.496962	13.0192	13.7931	14.1295	14.4328	14.9691	83	1.044
...	...	...	...	...	...	...	...	...	...	...
ypred[3]	14.4326	0.0903994	5.6887	3.38663	10.585	14.451	18.2019	25.6342	3960	0.999456
ypred[4]	14.3471	0.0899178	5.6869	3.39243	10.5848	14.3392	18.2295	25.5183	4000	1.00017
mu_new	14.208	0.0255003	1.1708	12.3481	13.8682	14.2873	14.5676	15.8755	2108	1.00535
ypred_new	14.2926	0.0919394	5.81476	2.84883	10.4361	14.4064	18.2223	25.4268	4000	1.00122
lp__	-743.541	1.47587	4.89491	-752.243	-746.688	-744.196	-741.133	-732.58	11	1.42308

In [10]:
```
# Print additional checking of the fit
print_compact_fit_checking(hier_uni_fit, hier_uni_df)
```

```
Maximum value of the Rhat:
1.423080255915649

Divergences:
308.0 of 4000 iterations ended with a divergence (7.7%)
Try running with larger adapt_delta to remove the divergences
```

Convergence diagnostic attempt 2

After changing the accuracy of the simulations from 0.9 to 0.93, the data is re-fit and following results are gained:

Diagnostic	Result
All $\hat{R}$ values close to 1	OK
Low $\hat{R}$ values combined with high effective sample size (n_eff)	OK
Divergences is 0	**NO** still 2% of the target posterior was not explored

With these results we can verify that the hierarchical uniform prior model fitting is almost successful. Although, this is not the desired result and therefore, in the next step the further improvement is discussed.

The results of the attempt 2 is shown below.

In [11]:
```
# Fit hierarchical uniform model
hier_uni_df, hier_uni_fit = compute_model(r'stan_code/hier_uniform_prior.stan',
                                          hierarchical_data_model, adapt_delta=0.93)
# Print the summary of the fit
print_compact_fit(hier_uni_df)
```

```
Using cached StanModel
```

Out[11]:

	mean	se_mean	sd	2.5%	25%	50%	75%	97.5%	n_eff	Rhat
mu0	14.1722	0.0133645	0.44123	13.3144	13.9179	14.159	14.4377	15.0467	1090	1.00438
sigma0	0.563965	0.0243783	0.571721	0.0510735	0.200409	0.40928	0.731901	2.12706	550	1.00114
mu[0]	14.0559	0.0143581	0.480942	13.0217	13.7558	14.0839	14.3739	14.9692	1122	1.0034
mu[1]	14.2551	0.013469	0.481318	13.3542	13.9509	14.2275	14.5544	15.2806	1277	1.00411
mu[2]	14.0422	0.0138805	0.481636	12.9916	13.76	14.056	14.3534	14.9512	1204	1.00298
...	...	...	...	...	...	...	...	...	...	...
ypred[3]	14.3333	0.0915444	5.68976	3.33591	10.4447	14.3595	18.0902	25.5877	3863	0.99995
ypred[4]	14.2131	0.0884799	5.58756	3.2083	10.4591	14.2649	18.0418	24.8965	3988	1.00015
mu_new	14.1864	0.0184552	0.961623	12.4116	13.7922	14.1716	14.569	16.0339	2715	1.00083
ypred_new	14.2098	0.0896986	5.67304	2.94677	10.4409	14.1165	17.8849	25.5395	4000	0.999853
lp__	-744.229	0.245898	4.09994	-752.034	-747.03	-744.541	-741.593	-735.542	278	1.00407

In [12]:
```
# Print additional checking of the fit
print_compact_fit_checking(hier_uni_fit, hier_uni_df)
```

```
Maximum value of the Rhat:
1.0043815114485763

Divergences:
79.0 of 4000 iterations ended with a divergence (1.975%)
Try running with larger adapt_delta to remove the divergences
```

6.3.2 Successful fitting

In this section, we will modify the Stan code and use exactly the same approach as described in pystan's workflow (http://mc-stan.org/users/documentation/case-studies/pystan_workflow.html (http://mc-stan.org/users/documentation/case-studies/pystan_workflow.html), A Successful Fit). Because the fit which uses the centered parametrization is not successful, we should change the Stan code using non-centered parametrization.

Centered parametrization of parameter *mu*

```
parameters {
  ...
  real mu[J]; // Tournament specific mu
  ...
}
model {
  for (j in 1:J) // Model for computing tournament specific mu from common mu0 and sigma0
    mu[j] ~ normal(mu0, sigma0);
  ...
}
```

is converted **to non-centered** parametrization

```
parameters {
  ...
  real mu_tilde[J];
}
transformed parameters {
  real mu[J];// Tournament specific mu
  for (j in 1:J)
    mu[j] = mu0 + sigma0 * mu_tilde[j];
}
model {
  for (j in 1:J) // Model for computing tournament specific mu from common mu0 and sigma0
    mu_tilde[j] ~ normal(0, 1); // Implies mu[j] ~ normal(mu0,sigma0)
  ...
}
```

The full updated Stan code is shown in the next section.

Stan model

The stan code of the model:

```
data {
  int<lower=0> N;  // Number of observations
  int<lower=0> J;  // Number of tournaments
  matrix[N,J] y;  // N observations for J tournaments
}
```

```
parameters {
  real mu0;             // Common mu for each J tournament's mu
  real<lower=0> sigma0; // Common std for each J tournament's mu
  real<lower=0> sigma; // Common std between tournaments
    real mu_tilde[J];
}
transformed parameters {
  real mu[J];          // Tournament specific mu
  for (j in 1:J)
    mu[j] = mu0 + sigma0 * mu_tilde[j];
}
model {
  for (j in 1:J)                    // Model for computing tournament specific mu from common m
u0 and sigma0
    mu_tilde[j] ~ normal(0, 1);    // Implies mu[j] ~ normal(mu0,sigma0)
  for (j in 1:J)
    y[:,j] ~ normal(mu[j], sigma); // Model for fitting data using machine specific mu and com
mon std
}
generated quantities {
  matrix[N,J] log_lik;
  real ypred[J];
  real mu_new;
  real ypred_new;

  for (j in 1:J)
     ypred[j] = normal_rng(mu[j], sigma);   // Predictive distibutions of all the tournaments
  mu_new = normal_rng(mu0, sigma0);       // Next posterior distribution from commonly learned
 mu0 and sigma0
  ypred_new = normal_rng(mu_new, sigma);    // Next predictive distibutions of new tournament

  for (j in 1:J)
     for (n in 1:N)
        log_lik[n,j] = normal_lpdf(y[n,j] | mu[j], sigma); //Log-likelihood
}
```

Convergence diagnostic attempt 3

The same procedure is followed (as in the previous section) and improved results were obtained:

Diagnostic	Result
All $\hat{R}$ values close to 1	OK
Low $\hat{R}$ values combined with high effective sample size (n_eff)	OK
Divergences is 0	GOOD ENOUGH still 0.025% of the target posterior was not expolred and increasing *adapt_delta* did not improve this result

All of these verify that hierarchical uniform prior model fitting is successful enough. The full fit can be found in the *Attachment 3* and a shorter summary is shown below.

In [13]:
```
# Fit hierarchical uniform model
hier_uni_df, hier_uni_fit = compute_model(r'stan_code/hier_uniform_prior_v2.stan', hiera
rchical_data_model)
# Print the summary of the fit
print_compact_fit(hier_uni_df)
```

```
Using cached StanModel
```

Out[13]:

	mean	se_mean	sd	2.5%	25%	50%	75%	97.5%	n_eff	R
mu0	14.1961	0.0141698	0.458058	13.2531	13.9249	14.1917	14.464	15.1017	1045	1.002
sigma0	0.550535	0.0179981	0.576781	0.0140076	0.18154	0.388406	0.717958	2.06309	1027	1.003
sigma	5.66836	0.00337786	0.213634	5.26576	5.52314	5.66113	5.80597	6.10786	4000	0.9997
mu_tilde[0]	-0.207582	0.0159645	0.883688	-1.97272	-0.795004	-0.21698	0.373531	1.49234	3064	0.9998
mu_tilde[1]	0.10843	0.0154156	0.883542	-1.68338	-0.477808	0.101281	0.691408	1.87599	3285	1.000
...	...	...	...	...	...	...	...	...	...	
ypred[3]	14.4115	0.0933838	5.77547	2.91519	10.6273	14.3439	18.2793	25.8232	3825	0.9998
ypred[4]	14.1985	0.0891236	5.63667	3.05899	10.3145	14.244	18.0424	24.8852	4000	0.9995
mu_new	14.2178	0.0179958	0.940442	12.446	13.8592	14.2051	14.5741	16.0938	2731	0.9997
ypred_new	14.198	0.0917411	5.80221	2.83785	10.2555	14.1872	18.1655	25.4919	4000	0.9997
lp__	-749.31	0.0670804	2.27085	-754.317	-750.67	-749.121	-747.698	-745.474	1146	1.001

In [14]:
```
print_compact_fit_checking(hier_uni_fit, hier_uni_df)
```

```
Maximum value of the Rhat:
1.0030853274280642

Divergences:
1.0 of 4000 iterations ended with a divergence (0.025%)
Try running with larger adapt_delta to remove the divergences
```

6.4 Hierarchical model with inverse gamma prior

Stan model

The stan code of the model (using non-centered parametrization):

```
data {
  int<lower=0> N;             // Number of observations
  int<lower=0> J;             // Number of tournaments
  matrix[N,J] y;              // N measurements for J tournaments
}
```

```
parameters {
  real mu0;             // Common mu for each J tournaments's mu
  real<lower=0> sigma0;         // Common std for each J tournament's mu
  real<lower=0> sigma;          // Common std
  real mu_tilde[J];
}
transformed parameters {
  real mu[J];           // Tournament specific mu
  for (j in 1:J)
    mu[j] = mu0 + sigma0 * mu_tilde[j];
}
model {
  for (j in 1:J) // Model for computing tournament specific mu from common mu0 and sigma0
    mu_tilde[j] ~ normal(0, 1); // Implies mu[j] ~ normal(mu0,sigma0)
  for (j in 1:J)
    y[:,j] ~ normal(mu[j], sigma);  // Model for fitting data using tournament specific mu and
 common std
}
generated quantities {
  matrix[N,J] log_lik;
  real ypred[J];
  real mu_new;
  real ypred_new;

  for (j in 1:J)
     ypred[j] = normal_rng(mu[j], sigma);   // Predictive distibutions of all the tournaments
  mu_new = normal_rng(mu0, sigma0); // Next posterior distribution from commonly learned mu0 a
nd sigma0
  ypred_new = normal_rng(mu_new, sigma);    // Next predictive distibutions of new tournament

  for (j in 1:J)
     for (n in 1:N)
        log_lik[n,j] = normal_lpdf(y[n,j] | mu[j], sigma); //Log-likelihood
}
```

Convergence diagnostic

The same procedure is followed (as in the previous section) and the diagnostic results are:

Diagnostic	Result
All $\hat{R}$ values close to 1	OK
Low $\hat{R}$ values combined with high effective sample size (n_eff)	OK
Divergences is 0	GOOD ENOUGH still 0.025% of the target posterior was not expolred and increasing *adapt_delta* did not improve this result

All of these verify that hierarchical inverse gamma prior model fitting is successful enough. The full fit can be found in the *Attachment 4* and a shorter summary is shown below.

In [15]:
```
# Fit hierarchical uniform model
hier_inv_df, hier_inv_fit = compute_model(r'stan_code/hier_inverse_gamma_prior_v2.stan',
 hierarchical_data_model)
print_compact_fit(hier_inv_df)
```

```
Using cached StanModel
```

Out[15]:

	mean	se_mean	sd	2.5%	25%	50%	75%	97.5%	n_eff	Rh
mu0	14.1742	0.0106244	0.429863	13.3323	13.9126	14.1783	14.4469	15.0025	1637	1.001
sigma0	0.55408	0.0187816	0.567502	0.0227001	0.193471	0.403468	0.728336	2.04482	913	1.00
mu_tilde[0]	-0.202636	0.0156438	0.883703	-1.96254	-0.760705	-0.211218	0.37144	1.55705	3191	1.00
mu_tilde[1]	0.115359	0.0161837	0.880342	-1.68287	-0.427827	0.10454	0.695337	1.82562	2959	1.000
mu_tilde[2]	-0.200715	0.0146266	0.857001	-1.93516	-0.749326	-0.218871	0.354451	1.48706	3433	1.000
...	...	...	...	...	...	...	...	...	...	
ypred[3]	14.5288	0.0921506	5.67531	3.5257	10.7779	14.5297	18.2851	26.0277	3793	0.9999
ypred[4]	14.1416	0.0893992	5.6541	3.05447	10.3961	14.0928	17.9503	25.1413	4000	0.9996
mu_new	14.1745	0.017315	0.895872	12.3202	13.8097	14.1975	14.5734	15.8751	2677	1.000
ypred_new	14.2066	0.0899841	5.69109	3.30853	10.3106	14.0458	18.1636	25.1357	4000	0.9996
lp__	-754.52	0.0668638	2.37343	-759.858	-756.017	-754.246	-752.799	-750.641	1260	1.001

In [16]:
```
print_compact_fit_checking(hier_inv_fit, hier_inv_df)
```

```
Maximum value of the Rhat:
1.0022963849717355

Divergences:
1.0 of 4000 iterations ended with a divergence (0.025%)
Try running with larger adapt_delta to remove the divergences
```

6.5 Conclusion

Based on the diagnostic results, all the four models can be used for further analysis (next section).

7 Model comparision with PSIS-LOO and P_{LOO-CV}

- Model selection according to the hightest LOO-CV sum
- Reliability based on the *k* values: < 0.7 ok, < 0.5 good

The PSIS-LOO values of the models can be computed using provided *psisloo* function. The function returns observation specific *k*-values and PSIS-LOO-CV values. In addition, it returns the sum of the PSIS-LOO-CV values, hence the sum of the LOO log desnities:

$$lppd_{loo-cv} = \sum_{i=1}^{N} log\left(\frac{1}{S}\sum_{s=1}^{S} p(y_i|\theta^{is})\right)$$

The estimated effective number of parameters (P_{LOO-CV}) in the model is computed as follows:

$$p_{loo-cv} = lppd - lppd_{loo-cv}$$

where $lppd$ is the sum of the log densities of the posterior draws:

$$lppd = \sum_{i=1}^{N} log\left(\frac{1}{S}\sum_{s=1}^{S} p(y_i|\theta^{s})\right)$$

Comparision

All the PSIS-LOO values, estimated effective number of parameters and *k*-values are shown below.

In [17]:
```
compare_psis_loo(fits=[pool_uni_fit, pool_inv_fit, hier_uni_fit, hier_inv_fit],  model_l
abels=[
        'Pooled model with uniform prior',
        'Pooled model with inverse gamma prior',
        'Hierarchical model with uniform prior',
        'Hierarchical model with inverse gamma prior'])
```

Out[17]:

	Models	Psisloo	P_eff	Max k value	Min k value	Mean k value
0	Pooled model with uniform prior	-1056.45	1.67	-0.07	-0.25	-0.18
1	Pooled model with inverse gamma prior	-1056.38	1.64	-0.01	-0.16	-0.11
2	Hierarchical model with uniform prior	-1057.25	2.96	0.10	-0.14	-0.05
3	Hierarchical model with inverse gamma prior	-1057.39	3.10	0.11	-0.18	-0.04

Conclusion

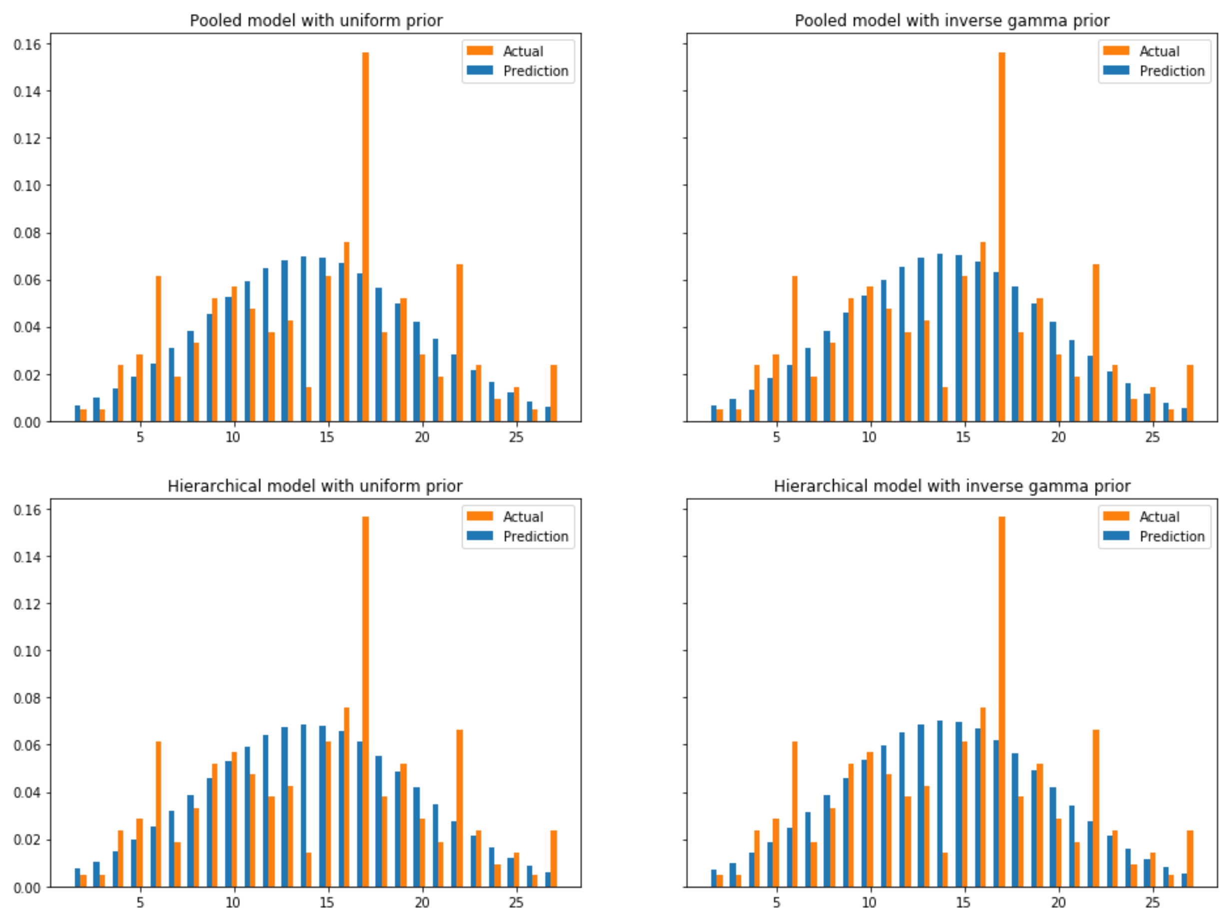
All the models are considered very reliable with very low k-values. If we consider towards model with best predictive accuracy, then **Pooled model with inverse gamma prior** should be selected, because its PSIS-LOO value is the highest (in other words the sum of log predictive density is the highest)

8 Posterior predictive checking

In this section, for all 4 models evaluated in the previous sessions, we will compare predictive distribution versus actual distribution for a new tournament

Comparision

In [18]:
```
compare_predictive_vs_actual(fits=[pool_uni_fit, pool_inv_fit, hier_uni_fit, hier_inv_fi
t], labels=[
        'Pooled model with uniform prior',
        'Pooled model with inverse gamma prior',
        'Hierarchical model with uniform prior',
        'Hierarchical model with inverse gamma prior'],
     ypred_accessors= ['ypred', 'ypred', 'ypred_new', 'ypred_new'], new_data=last)
```



Observation

Posterior predictive distribution are almost identical among all models. This can be guessed already in session 3, where the data can be seen to by highly consistent throughout different tournaments.

Errors are considerable between prediction and actual distribution. Albeit the posterior of the estimand seems to follow a normal distribution, the amount of data in only one new tournament is too small to construct a normal distribution, hence the difference between prediction and actual values.

9 Conclusion

Problems

- Data model cannot be used for direct inference of a single match
- The values of the divergences for the hierarchical models were 0.025% instead of exact 0% (0.025% of the target posterior was not explored). Because the value is quite small, we decided to use the hierarchical models in the further analysis.

Potential improvements

- Given the outcome of this report, binomial can be a good fit as well
- Data model can be improved so that the estimand is a joint distribution of some parameters (e.g. absolute ranking + win degree)
- Data model can be modified to fit with multinomial model
- Prior and model analysis could be improved by adding the sensitivity analysis

Discussion

From the badminton domain perspective, the result is satisfiable:

- There is a visible correlation between ranking spread and win degree
- Probability of extreme outcome (towards 1 or 28) are low, and not expected in the tournament

From the statistical inference perspective, the result is also satisfiable

- Given the domain knowledge, one would expect the distribution of the estimand to be a normal distribution
- Given the found posteriors, we can see the result is highly data-driven
- Given two models, pooled and hierarchical, we can see that hierarchical model ends up as pooled model

---

Source code

In [1]:
```
# Import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
from scipy import stats
import pystan
import stan_utility
import psis
import warnings
# For hiding warnings that do not effect the functionality of the code
warnings.filterwarnings('ignore')
```

In [20]:
```
# Data is provided as files, 1 file contains all matches result of a tournament
# We will use data from all tournaments to fit model
# Except for the last one which will be used to evaluate prediction accuracy
data = []
filenames = os.listdir(r'./data/')
for idx, filename in enumerate(filenames):
    col = np.loadtxt(f'data//{filename}').tolist()
    if (idx == (len(filenames) - 1)):
        last = col
    else:
        data.append(col[0:67])
np_data = np.array(data)

# Show the data in dataframe and change the names of the rows and columns to more descri
able
def show_first_rows_of_data():
    df = pd.DataFrame(np_data.T)
    df.columns=['Tournament '+str(i+1) for i in range(np_data.shape[0])]
    df = df.rename({i: 'Match '+str(i+1) for i in range(np_data.shape[1])}, axis='index'
)
    return df.head()

# Show the data summary: mean, min, max, ....
def show_summary_of_data():
    df = pd.DataFrame(np_data.T)
    df.columns=['Tournament '+str(i+1) for i in range(np_data.shape[0])]
    return df.describe()

# Pooled data and its model for Stan compiler
pooled_data = np_data.flatten()
pooled_data_model = dict(N=len(pooled_data), y=pooled_data, alpha=1, beta=1)
#pooled_inv_g_data_model = dict(N=len(pooled_data), y=pooled_data)

# Hierarchical data (np_data.T) and its model for Stan compiler
hierarchical_data_model = dict(N = np_data.shape[1], J= np_data.shape[0],y = np_data.T,
alpha=1, beta=1)

# Compile the given model and fit the given data.
# Parameters:
#     file_path: ''
#         The path of the stan model code
#     data: numpy array
#         The data to be fitted
#     adapt_delta: 0...1
#        Effects to divergences, hence to the accuracy of the posterior.
#        The smaller the value is the more strict the Stan model is in accepting sampel
s.
#        The bigger the value is the easier the Stan model accepts samples.
# Returns the summary of the fit and the fit itself.
def compute_model(file_path, data, adapt_delta=0.9):

    # Compile model for both separated and pooled
    model = stan_utility.compile_model(file_path)

    # Fit model: adapt_delta is used for divergences
    fit = model.sampling(data=data, seed=194838,control=dict(adapt_delta=adapt_delta))

    # get summary of the fit, use pandas data frame for layout
    summary = fit.summary()
    df = pd.DataFrame(summary['summary'], index=summary['summary_rownames'], columns=sum
mary['summary_colnames'])

    return df, fit
```

```python
# Show compact details of the fit instead of showing the whole fit
def print_compact_fit(fit_df, number_of_rows_head=5, number_of_rows_tail=5):
    df = fit_df.head(number_of_rows_head)
    df = df.append([{'mean':'...','se_mean':'...','sd':'...','2.5%':'...','25%':'...',
                    '50%':'...','75%':'...','97.5%':'...','n_eff':'...','Rhat':'...'}])
    df = df.rename({0: '...'}, axis='index')
    df = df.append(fit_df.tail(number_of_rows_tail))
    return df

# Show key details of the checking of the fit: rhat and divergences
def print_compact_fit_checking(fit, df):
    #Check the maximum value of the Rhat
    print("Maximum value of the Rhat: ")
    print(df.describe()['Rhat'][7])
    print("")

    # Check divergences
    print("Divergences:")
    stan_utility.check_div(fit)
    print("")

# Compare PSIS-LOO values
def compare_psis_loo(fits, model_labels):
    psis_loos, p_effs, k_max, k_min, k_mean = [], [], [], [], []
    for fit in fits:
        psis_loo, p_eff, ks = extract_psis_loo(fit)
        psis_loos.append(psis_loo)
        p_effs.append(p_eff)
        k_max.append(np.max(ks))
        k_min.append(np.min(ks))
        k_mean.append(np.mean(ks))

    df = pd.DataFrame({
        'Models': model_labels,
        'Psisloo': psis_loos,
        'P_eff': p_effs,
        'Max k value': k_max,
        'Min k value': k_min,
        'Mean k value': k_mean
    })

    return df.round(2)

# Get the effective sample size of the parameters
def get_p_eff(log_lik, lppd_loocv):
    likelihoods = np.asarray([np.exp(log_likelihood.flatten()) for log_likelihood in log
_lik])
    num_sim, num_obs = likelihoods.shape
    lppd = 0
    for obs in range(num_obs):
        lppd += np.log(np.sum(likelihoods[:, obs]) / num_sim)

    p_eff = lppd - lppd_loocv
    return p_eff

def extract_psis_loo(samples, plot_title=''):
    log_lik_matrix = np.asarray([single_sample.flatten() for single_sample in samples['l
og_lik']])
    loo, loos, ks = psis.psisloo(log_lik_matrix)

    # Calculate p_eff
    p_eff = get_p_eff(log_lik_matrix, loo)
```

```python
    return loo, p_eff, ks

def compare_predictive_vs_actual(fits, labels, ypred_accessors, new_data):
    bar_width = 0.3
    fig, axes = plt.subplots(nrows=2, ncols=2, sharey=True,figsize=(16,12), subplot_kw=d
ict(aspect='auto'))
    plots = [axes[0,0], axes[0,1], axes[1,0], axes[1,1]]

    # Group new_data
    # e.g. [1,2,3,2,2] => [1: 0.2, 2: 0.6, 3: 0.2]
    aggregated = dict()
    for i in new_data:
        if i in aggregated:
            aggregated[i] += 1
        else:
            aggregated[i] = 1

    # Dist of new_data
    x = np.array(list(aggregated.keys()))
    y = np.array(list(aggregated.values())) / len(new_data)

    for i in range(0, len(fits)):
        fit = fits[i]
        label = labels[i]
        ypred_accessor = ypred_accessors[i]
        ypred = fit.extract(permuted=True)[ypred_accessor]

        # Dist of ypred for new_data values
        y2_dist = stats.norm(np.mean(ypred), np.std(ypred))
        y2 = y2_dist.pdf(x)

        partial_plt = plots[i]
        partial_plt.bar(x,y,width=bar_width,label="Actual", color="C1")
        partial_plt.bar(x-bar_width,y2,width=bar_width,label="Prediction", color="C0")
        partial_plt.set_title(label)
        partial_plt.legend()

    plt.show()

def show_attachments():
    print("##########################################################################")
    print("########## Attachment 1: Fit of pooled model with uniform prior ##########")
    print("##########################################################################")
    print(""); print(pool_uni_fit); print("");
    print("##########################################################################")
    print("####### Attachment 2: Fit of pooled model with inverse gamma prior #######")
    print("##########################################################################")
    print(""); print(pool_inv_fit); print("");
    print("##########################################################################")
    print("####### Attachment 3: Fit of hierarchical model with uniform prior #######")
    print("##########################################################################")
    print(""); print(hier_uni_fit); print("")
    print("##########################################################################")
    print("#### Attachment 4: Fit of hierarchical model with inverse gamma prior ####")
    print("##########################################################################")
    print(""); print(hier_inv_fit); print("");

#show_attachments()
```

```
########################################################################
########## Attachment 1: Fit of pooled model with uniform prior ##########
########################################################################

Inference for Stan model: anon_model_9b8e95f23a292c6baefb5978c5223890.
4 chains, each with iter=2000; warmup=1000; thin=1;
post-warmup draws per chain=1000, total post-warmup draws=4000.

               mean se_mean     sd   2.5%    25%    50%    75%  97.5%  n_eff   Rhat
mu            14.19  6.0e-3   0.31  13.56  13.98   14.2  14.41  14.82   2712    1.0
sigma          5.66  4.4e-3   0.22   5.24   5.51   5.65   5.81   6.13   2577    1.0
log_lik[0]    -3.71  1.8e-3   0.09  -3.89  -3.77   -3.7  -3.64  -3.53   2641    1.0
log_lik[1]    -2.66  7.8e-4   0.04  -2.74  -2.69  -2.66  -2.64  -2.59   2547    1.0
log_lik[2]     -2.7  7.9e-4   0.04  -2.79  -2.73   -2.7  -2.68  -2.63   2483    1.0
log_lik[3]    -2.66  7.8e-4   0.04  -2.74  -2.69  -2.66  -2.64  -2.59   2547    1.0
log_lik[4]    -3.02  9.3e-4   0.05  -3.12  -3.05  -3.01  -2.98  -2.92   2698    1.0
log_lik[5]    -2.78  8.1e-4   0.04  -2.86   -2.8  -2.78  -2.75   -2.7   2484    1.0
log_lik[6]    -2.78  8.1e-4   0.04  -2.86   -2.8  -2.78  -2.75   -2.7   2484    1.0
log_lik[7]    -2.78  8.1e-4   0.04  -2.86   -2.8  -2.78  -2.75   -2.7   2484    1.0
log_lik[8]    -3.98  2.2e-3   0.11  -4.21  -4.05  -3.97   -3.9  -3.76   2595    1.0
log_lik[9]    -2.78  8.1e-4   0.04  -2.86   -2.8  -2.78  -2.75   -2.7   2484    1.0
log_lik[10]   -2.78  8.1e-4   0.04  -2.86   -2.8  -2.78  -2.75   -2.7   2484    1.0
log_lik[11]   -3.08  9.7e-4   0.05  -3.18  -3.11  -3.08  -3.04  -2.98   2793    1.0
log_lik[12]   -3.71  1.8e-3   0.09  -3.89  -3.77   -3.7  -3.64  -3.53   2641    1.0
log_lik[13]   -2.78  8.1e-4   0.04  -2.86   -2.8  -2.78  -2.75   -2.7   2484    1.0
log_lik[14]   -3.98  2.2e-3   0.11  -4.21  -4.05  -3.97   -3.9  -3.76   2595    1.0
log_lik[15]   -3.71  1.8e-3   0.09  -3.89  -3.77   -3.7  -3.64  -3.53   2641    1.0
log_lik[16]   -2.81  7.7e-4   0.04  -2.89  -2.84  -2.81  -2.78  -2.73   2911    1.0
log_lik[17]   -3.08  9.7e-4   0.05  -3.18  -3.11  -3.08  -3.04  -2.98   2793    1.0
log_lik[18]    -2.7  7.9e-4   0.04  -2.79  -2.73   -2.7  -2.68  -2.63   2483    1.0
log_lik[19]   -3.38  1.3e-3   0.07  -3.52  -3.43  -3.38  -3.33  -3.25   2803    1.0
log_lik[20]   -2.78  8.1e-4   0.04  -2.86   -2.8  -2.78  -2.75   -2.7   2484    1.0
log_lik[21]   -2.66  7.8e-4   0.04  -2.74  -2.69  -2.66  -2.64  -2.59   2547    1.0
log_lik[22]   -4.16  2.3e-3   0.13  -4.42  -4.24  -4.15  -4.07  -3.94   2920    1.0
log_lik[23]   -2.93  8.4e-4   0.05  -3.02  -2.96  -2.93   -2.9  -2.84   2853    1.0
log_lik[24]   -3.08  9.7e-4   0.05  -3.18  -3.11  -3.08  -3.04  -2.98   2793    1.0
log_lik[25]   -3.25  1.2e-3   0.06  -3.38   -3.3  -3.25  -3.21  -3.14   2754    1.0
log_lik[26]   -3.61  1.6e-3   0.08  -3.78  -3.66   -3.6  -3.55  -3.46   2853    1.0
log_lik[27]   -2.73  7.4e-4   0.04  -2.81  -2.76  -2.73   -2.7  -2.65   2942    1.0
log_lik[28]   -3.02  9.3e-4   0.05  -3.12  -3.05  -3.01  -2.98  -2.92   2698    1.0
log_lik[29]   -3.08  9.7e-4   0.05  -3.18  -3.11  -3.08  -3.04  -2.98   2793    1.0
log_lik[30]   -2.66  7.8e-4   0.04  -2.74  -2.69  -2.66  -2.64  -2.59   2547    1.0
log_lik[31]   -2.73  7.4e-4   0.04  -2.81  -2.76  -2.73   -2.7  -2.65   2942    1.0
log_lik[32]   -3.25  1.2e-3   0.06  -3.38   -3.3  -3.25  -3.21  -3.14   2754    1.0
log_lik[33]   -2.78  8.1e-4   0.04  -2.86   -2.8  -2.78  -2.75   -2.7   2484    1.0
log_lik[34]   -2.66  7.8e-4   0.04  -2.74  -2.69  -2.66  -2.64  -2.59   2547    1.0
log_lik[35]   -4.48  2.8e-3   0.15  -4.79  -4.58  -4.48  -4.38  -4.21   2940    1.0
log_lik[36]   -3.02  9.3e-4   0.05  -3.12  -3.05  -3.01  -2.98  -2.92   2698    1.0
log_lik[37]   -4.16  2.3e-3   0.13  -4.42  -4.24  -4.15  -4.07  -3.94   2920    1.0
log_lik[38]    -2.7  7.9e-4   0.04  -2.79  -2.73   -2.7  -2.68  -2.63   2483    1.0
log_lik[39]   -3.98  2.2e-3   0.11  -4.21  -4.05  -3.97   -3.9  -3.76   2595    1.0
log_lik[40]   -2.78  8.1e-4   0.04  -2.86   -2.8  -2.78  -2.75   -2.7   2484    1.0
log_lik[41]   -3.18  1.1e-3   0.06   -3.3  -3.22  -3.18  -3.14  -3.07   2746    1.0
log_lik[42]   -3.25  1.2e-3   0.06  -3.38   -3.3  -3.25  -3.21  -3.14   2754    1.0
log_lik[43]   -3.61  1.6e-3   0.08  -3.78  -3.66   -3.6  -3.55  -3.46   2853    1.0
log_lik[44]   -2.66  7.8e-4   0.04  -2.74  -2.69  -2.66  -2.64  -2.59   2547    1.0
log_lik[45]   -3.71  1.8e-3   0.09  -3.89  -3.77   -3.7  -3.64  -3.53   2641    1.0
log_lik[46]   -3.71  1.8e-3   0.09  -3.89  -3.77   -3.7  -3.64  -3.53   2641    1.0
log_lik[47]   -3.08  9.7e-4   0.05  -3.18  -3.11  -3.08  -3.04  -2.98   2793    1.0
log_lik[48]   -3.25  1.2e-3   0.06  -3.38   -3.3  -3.25  -3.21  -3.14   2754    1.0
log_lik[49]   -2.78  8.1e-4   0.04  -2.86   -2.8  -2.78  -2.75   -2.7   2484    1.0
log_lik[50]   -3.38  1.3e-3   0.07  -3.52  -3.43  -3.38  -3.33  -3.25   2803    1.0
log_lik[51]   -3.02  9.3e-4   0.05  -3.12  -3.05  -3.01  -2.98  -2.92   2698    1.0
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log_lik[52]	-3.61	1.6e-3	0.08	-3.78	-3.66	-3.6	-3.55	-3.46	2853	1.0
log_lik[53]	-4.28	2.6e-3	0.13	-4.56	-4.37	-4.28	-4.19	-4.02	2565	1.0
log_lik[54]	-3.08	9.7e-4	0.05	-3.18	-3.11	-3.08	-3.04	-2.98	2793	1.0
log_lik[55]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[56]	-2.88	8.5e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2565	1.0
log_lik[57]	-2.73	7.4e-4	0.04	-2.81	-2.76	-2.73	-2.7	-2.65	2942	1.0
log_lik[58]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[59]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[60]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[61]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[62]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[63]	-3.46	1.4e-3	0.07	-3.62	-3.51	-3.46	-3.41	-3.32	2738	1.0
log_lik[64]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[65]	-3.18	1.1e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2746	1.0
log_lik[66]	-3.61	1.6e-3	0.08	-3.78	-3.66	-3.6	-3.55	-3.46	2853	1.0
log_lik[67]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[68]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[69]	-3.46	1.4e-3	0.07	-3.62	-3.51	-3.46	-3.41	-3.32	2738	1.0
log_lik[70]	-2.68	7.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	2661	1.0
log_lik[71]	-3.18	1.1e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2746	1.0
log_lik[72]	-3.18	1.1e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2746	1.0
log_lik[73]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[74]	-5.22	3.8e-3	0.21	-5.65	-5.36	-5.22	-5.08	-4.85	2963	1.0
log_lik[75]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[76]	-2.73	7.4e-4	0.04	-2.81	-2.76	-2.73	-2.7	-2.65	2942	1.0
log_lik[77]	-2.65	7.8e-4	0.04	-2.73	-2.68	-2.65	-2.63	-2.58	2561	1.0
log_lik[78]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[79]	-3.38	1.3e-3	0.07	-3.52	-3.43	-3.38	-3.33	-3.25	2803	1.0
log_lik[80]	-3.46	1.4e-3	0.07	-3.62	-3.51	-3.46	-3.41	-3.32	2738	1.0
log_lik[81]	-2.81	7.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.73	2911	1.0
log_lik[82]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[83]	-2.68	7.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	2661	1.0
log_lik[84]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[85]	-2.73	7.4e-4	0.04	-2.81	-2.76	-2.73	-2.7	-2.65	2942	1.0
log_lik[86]	-3.02	9.3e-4	0.05	-3.12	-3.05	-3.01	-2.98	-2.92	2698	1.0
log_lik[87]	-3.18	1.1e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2746	1.0
log_lik[88]	-2.88	8.5e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2565	1.0
log_lik[89]	-4.16	2.3e-3	0.13	-4.42	-4.24	-4.15	-4.07	-3.94	2920	1.0
log_lik[90]	-3.08	9.7e-4	0.05	-3.18	-3.11	-3.08	-3.04	-2.98	2793	1.0
log_lik[91]	-2.68	7.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	2661	1.0
log_lik[92]	-2.88	8.5e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2565	1.0
log_lik[93]	-3.38	1.3e-3	0.07	-3.52	-3.43	-3.38	-3.33	-3.25	2803	1.0
log_lik[94]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[95]	-2.65	7.8e-4	0.04	-2.73	-2.68	-2.65	-2.63	-2.58	2561	1.0
log_lik[96]	-3.08	9.7e-4	0.05	-3.18	-3.11	-3.08	-3.04	-2.98	2793	1.0
log_lik[97]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[98]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[99]	-4.62	3.1e-3	0.16	-4.95	-4.72	-4.61	-4.51	-4.3	2548	1.0
log_lik[100]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[101]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[102]	-3.18	1.1e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2746	1.0
log_lik[103]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[104]	-4.48	2.8e-3	0.15	-4.79	-4.58	-4.48	-4.38	-4.21	2940	1.0
log_lik[105]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[106]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[107]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[108]	-3.46	1.4e-3	0.07	-3.62	-3.51	-3.46	-3.41	-3.32	2738	1.0
log_lik[109]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[110]	-3.08	9.7e-4	0.05	-3.18	-3.11	-3.08	-3.04	-2.98	2793	1.0
log_lik[111]	-2.65	7.8e-4	0.04	-2.73	-2.68	-2.65	-2.63	-2.58	2561	1.0
log_lik[112]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[113]	-2.68	7.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	2661	1.0
log_lik[114]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[115]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0

log_lik[116]	-2.88	8.5e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2565	1.0
log_lik[117]	-4.48	2.8e-3	0.15	-4.79	-4.58	-4.48	-4.38	-4.21	2940	1.0
log_lik[118]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[119]	-3.61	1.6e-3	0.08	-3.78	-3.66	-3.6	-3.55	-3.46	2853	1.0
log_lik[120]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[121]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[122]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[123]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[124]	-2.81	7.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.73	2911	1.0
log_lik[125]	-3.61	1.6e-3	0.08	-3.78	-3.66	-3.6	-3.55	-3.46	2853	1.0
log_lik[126]	-2.88	8.5e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2565	1.0
log_lik[127]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[128]	-2.68	7.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	2661	1.0
log_lik[129]	-4.28	2.6e-3	0.13	-4.56	-4.37	-4.28	-4.19	-4.02	2565	1.0
log_lik[130]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[131]	-2.88	8.5e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2565	1.0
log_lik[132]	-3.18	1.1e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2746	1.0
log_lik[133]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[134]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[135]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[136]	-4.28	2.6e-3	0.13	-4.56	-4.37	-4.28	-4.19	-4.02	2565	1.0
log_lik[137]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[138]	-3.18	1.1e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2746	1.0
log_lik[139]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[140]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[141]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[142]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[143]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[144]	-3.98	2.2e-3	0.11	-4.21	-4.05	-3.97	-3.9	-3.76	2595	1.0
log_lik[145]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[146]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[147]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[148]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[149]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[150]	-2.81	7.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.73	2911	1.0
log_lik[151]	-3.08	9.7e-4	0.05	-3.18	-3.11	-3.08	-3.04	-2.98	2793	1.0
log_lik[152]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[153]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[154]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[155]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[156]	-3.61	1.6e-3	0.08	-3.78	-3.66	-3.6	-3.55	-3.46	2853	1.0
log_lik[157]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[158]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[159]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[160]	-3.61	1.6e-3	0.08	-3.78	-3.66	-3.6	-3.55	-3.46	2853	1.0
log_lik[161]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[162]	-3.87	1.9e-3	0.1	-4.08	-3.94	-3.86	-3.8	-3.68	2892	1.0
log_lik[163]	-3.02	9.3e-4	0.05	-3.12	-3.05	-3.01	-2.98	-2.92	2698	1.0
log_lik[164]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[165]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[166]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[167]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[168]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[169]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[170]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[171]	-4.84	3.3e-3	0.18	-5.2	-4.96	-4.83	-4.71	-4.52	2953	1.0
log_lik[172]	-2.68	7.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	2661	1.0
log_lik[173]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[174]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[175]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[176]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[177]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[178]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[179]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0

log_lik[180]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[181]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[182]	-2.81	7.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.73	2911	1.0
log_lik[183]	-3.87	1.9e-3	0.1	-4.08	-3.94	-3.86	-3.8	-3.68	2892	1.0
log_lik[184]	-3.18	1.1e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2746	1.0
log_lik[185]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[186]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[187]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[188]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[189]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[190]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[191]	-4.16	2.3e-3	0.13	-4.42	-4.24	-4.15	-4.07	-3.94	2920	1.0
log_lik[192]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[193]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[194]	-2.73	7.4e-4	0.04	-2.81	-2.76	-2.73	-2.7	-2.65	2942	1.0
log_lik[195]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[196]	-2.68	7.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	2661	1.0
log_lik[197]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[198]	-2.65	7.8e-4	0.04	-2.73	-2.68	-2.65	-2.63	-2.58	2561	1.0
log_lik[199]	-2.68	7.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	2661	1.0
log_lik[200]	-3.98	2.2e-3	0.11	-4.21	-4.05	-3.97	-3.9	-3.76	2595	1.0
log_lik[201]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[202]	-2.68	7.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	2661	1.0
log_lik[203]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[204]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[205]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[206]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[207]	-4.16	2.3e-3	0.13	-4.42	-4.24	-4.15	-4.07	-3.94	2920	1.0
log_lik[208]	-4.84	3.3e-3	0.18	-5.2	-4.96	-4.83	-4.71	-4.52	2953	1.0
log_lik[209]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[210]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[211]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[212]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[213]	-3.98	2.2e-3	0.11	-4.21	-4.05	-3.97	-3.9	-3.76	2595	1.0
log_lik[214]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[215]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[216]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[217]	-3.08	9.7e-4	0.05	-3.18	-3.11	-3.08	-3.04	-2.98	2793	1.0
log_lik[218]	-4.28	2.6e-3	0.13	-4.56	-4.37	-4.28	-4.19	-4.02	2565	1.0
log_lik[219]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[220]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[221]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[222]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[223]	-3.61	1.6e-3	0.08	-3.78	-3.66	-3.6	-3.55	-3.46	2853	1.0
log_lik[224]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[225]	-3.38	1.3e-3	0.07	-3.52	-3.43	-3.38	-3.33	-3.25	2803	1.0
log_lik[226]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[227]	-3.61	1.6e-3	0.08	-3.78	-3.66	-3.6	-3.55	-3.46	2853	1.0
log_lik[228]	-3.02	9.3e-4	0.05	-3.12	-3.05	-3.01	-2.98	-2.92	2698	1.0
log_lik[229]	-3.38	1.3e-3	0.07	-3.52	-3.43	-3.38	-3.33	-3.25	2803	1.0
log_lik[230]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[231]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[232]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[233]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[234]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[235]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[236]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[237]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[238]	-5.22	3.8e-3	0.21	-5.65	-5.36	-5.22	-5.08	-4.85	2963	1.0
log_lik[239]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[240]	-2.81	7.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.73	2911	1.0
log_lik[241]	-3.08	9.7e-4	0.05	-3.18	-3.11	-3.08	-3.04	-2.98	2793	1.0
log_lik[242]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[243]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0

log_lik[244]	-4.84	3.3e-3	0.18	-5.2	-4.96	-4.83	-4.71	-4.52	2953	1.0
log_lik[245]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[246]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[247]	-2.73	7.4e-4	0.04	-2.81	-2.76	-2.73	-2.7	-2.65	2942	1.0
log_lik[248]	-2.81	7.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.73	2911	1.0
log_lik[249]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[250]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[251]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[252]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[253]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[254]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[255]	-2.81	7.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.73	2911	1.0
log_lik[256]	-4.62	3.1e-3	0.16	-4.95	-4.72	-4.61	-4.51	-4.3	2548	1.0
log_lik[257]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[258]	-3.38	1.3e-3	0.07	-3.52	-3.43	-3.38	-3.33	-3.25	2803	1.0
log_lik[259]	-4.16	2.3e-3	0.13	-4.42	-4.24	-4.15	-4.07	-3.94	2920	1.0
log_lik[260]	-3.61	1.6e-3	0.08	-3.78	-3.66	-3.6	-3.55	-3.46	2853	1.0
log_lik[261]	-3.61	1.6e-3	0.08	-3.78	-3.66	-3.6	-3.55	-3.46	2853	1.0
log_lik[262]	-2.81	7.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.73	2911	1.0
log_lik[263]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[264]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[265]	-3.61	1.6e-3	0.08	-3.78	-3.66	-3.6	-3.55	-3.46	2853	1.0
log_lik[266]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[267]	-3.61	1.6e-3	0.08	-3.78	-3.66	-3.6	-3.55	-3.46	2853	1.0
log_lik[268]	-5.38	4.3e-3	0.22	-5.83	-5.52	-5.37	-5.23	-4.96	2533	1.0
log_lik[269]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[270]	-3.98	2.2e-3	0.11	-4.21	-4.05	-3.97	-3.9	-3.76	2595	1.0
log_lik[271]	-2.68	7.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	2661	1.0
log_lik[272]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[273]	-3.18	1.1e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2746	1.0
log_lik[274]	-3.18	1.1e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2746	1.0
log_lik[275]	-3.87	1.9e-3	0.1	-4.08	-3.94	-3.86	-3.8	-3.68	2892	1.0
log_lik[276]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[277]	-2.88	8.5e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2565	1.0
log_lik[278]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[279]	-4.28	2.6e-3	0.13	-4.56	-4.37	-4.28	-4.19	-4.02	2565	1.0
log_lik[280]	-2.81	7.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.73	2911	1.0
log_lik[281]	-3.25	1.2e-3	0.06	-3.38	-3.3	-3.25	-3.21	-3.14	2754	1.0
log_lik[282]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[283]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[284]	-3.18	1.1e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2746	1.0
log_lik[285]	-3.18	1.1e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2746	1.0
log_lik[286]	-5.22	3.8e-3	0.21	-5.65	-5.36	-5.22	-5.08	-4.85	2963	1.0
log_lik[287]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[288]	-2.68	7.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	2661	1.0
log_lik[289]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[290]	-2.81	7.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.73	2911	1.0
log_lik[291]	-2.73	7.4e-4	0.04	-2.81	-2.76	-2.73	-2.7	-2.65	2942	1.0
log_lik[292]	-2.93	8.4e-4	0.05	-3.02	-2.96	-2.93	-2.9	-2.84	2853	1.0
log_lik[293]	-2.68	7.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	2661	1.0
log_lik[294]	-4.62	3.1e-3	0.16	-4.95	-4.72	-4.61	-4.51	-4.3	2548	1.0
log_lik[295]	-3.71	1.8e-3	0.09	-3.89	-3.77	-3.7	-3.64	-3.53	2641	1.0
log_lik[296]	-3.08	9.7e-4	0.05	-3.18	-3.11	-3.08	-3.04	-2.98	2793	1.0
log_lik[297]	-2.66	7.8e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	2547	1.0
log_lik[298]	-3.61	1.6e-3	0.08	-3.78	-3.66	-3.6	-3.55	-3.46	2853	1.0
log_lik[299]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[300]	-2.88	8.5e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2565	1.0
log_lik[301]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[302]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[303]	-4.28	2.6e-3	0.13	-4.56	-4.37	-4.28	-4.19	-4.02	2565	1.0
log_lik[304]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0
log_lik[305]	-2.68	7.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	2661	1.0
log_lik[306]	-2.78	8.1e-4	0.04	-2.86	-2.8	-2.78	-2.75	-2.7	2484	1.0
log_lik[307]	-2.7	7.9e-4	0.04	-2.79	-2.73	-2.7	-2.68	-2.63	2483	1.0

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log_lik[308]  -2.88  8.5e-4   0.04  -2.97  -2.91  -2.88  -2.85   -2.8   2565    1.0
log_lik[309]  -3.71  1.8e-3   0.09  -3.89  -3.77   -3.7  -3.64  -3.53   2641    1.0
log_lik[310]   -2.7  7.9e-4   0.04  -2.79  -2.73   -2.7  -2.68  -2.63   2483    1.0
log_lik[311]   -2.7  7.9e-4   0.04  -2.79  -2.73   -2.7  -2.68  -2.63   2483    1.0
log_lik[312]  -3.25  1.2e-3   0.06  -3.38   -3.3  -3.25  -3.21  -3.14   2754    1.0
log_lik[313]   -2.7  7.9e-4   0.04  -2.79  -2.73   -2.7  -2.68  -2.63   2483    1.0
log_lik[314]  -3.61  1.6e-3   0.08  -3.78  -3.66   -3.6  -3.55  -3.46   2853    1.0
log_lik[315]  -2.88  8.5e-4   0.04  -2.97  -2.91  -2.88  -2.85   -2.8   2565    1.0
log_lik[316]  -3.61  1.6e-3   0.08  -3.78  -3.66   -3.6  -3.55  -3.46   2853    1.0
log_lik[317]  -3.71  1.8e-3   0.09  -3.89  -3.77   -3.7  -3.64  -3.53   2641    1.0
log_lik[318]  -2.66  7.8e-4   0.04  -2.74  -2.69  -2.66  -2.64  -2.59   2547    1.0
log_lik[319]   -2.7  7.9e-4   0.04  -2.79  -2.73   -2.7  -2.68  -2.63   2483    1.0
log_lik[320]   -2.7  7.9e-4   0.04  -2.79  -2.73   -2.7  -2.68  -2.63   2483    1.0
log_lik[321]  -3.71  1.8e-3   0.09  -3.89  -3.77   -3.7  -3.64  -3.53   2641    1.0
log_lik[322]  -2.65  7.8e-4   0.04  -2.73  -2.68  -2.65  -2.63  -2.58   2561    1.0
log_lik[323]  -2.81  7.7e-4   0.04  -2.89  -2.84  -2.81  -2.78  -2.73   2911    1.0
log_lik[324]  -2.78  8.1e-4   0.04  -2.86   -2.8  -2.78  -2.75   -2.7   2484    1.0
log_lik[325]  -2.73  7.4e-4   0.04  -2.81  -2.76  -2.73   -2.7  -2.65   2942    1.0
log_lik[326]  -3.25  1.2e-3   0.06  -3.38   -3.3  -3.25  -3.21  -3.14   2754    1.0
log_lik[327]  -2.93  8.4e-4   0.05  -3.02  -2.96  -2.93   -2.9  -2.84   2853    1.0
log_lik[328]  -2.78  8.1e-4   0.04  -2.86   -2.8  -2.78  -2.75   -2.7   2484    1.0
log_lik[329]  -4.84  3.3e-3   0.18   -5.2  -4.96  -4.83  -4.71  -4.52   2953    1.0
log_lik[330]  -3.38  1.3e-3   0.07  -3.52  -3.43  -3.38  -3.33  -3.25   2803    1.0
log_lik[331]  -3.61  1.6e-3   0.08  -3.78  -3.66   -3.6  -3.55  -3.46   2853    1.0
log_lik[332]   -2.7  7.9e-4   0.04  -2.79  -2.73   -2.7  -2.68  -2.63   2483    1.0
log_lik[333]  -2.81  7.7e-4   0.04  -2.89  -2.84  -2.81  -2.78  -2.73   2911    1.0
log_lik[334]  -3.46  1.4e-3   0.07  -3.62  -3.51  -3.46  -3.41  -3.32   2738    1.0
ypred         14.29    0.09    5.7   3.43  10.36  14.28   18.2   25.6   4000    1.0
lp__         -746.0    0.02   1.01 -748.7 -746.4 -745.7 -745.3 -745.0   1637    1.0

Samples were drawn using NUTS at Sun Dec  9 13:47:05 2018.
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).

########################################################################
####### Attachment 2: Fit of pooled model with inverse gamma prior #######
########################################################################

Inference for Stan model: anon_model_fa6169eb72725ff16af37d26935097d5.
4 chains, each with iter=2000; warmup=1000; thin=1;
post-warmup draws per chain=1000, total post-warmup draws=4000.

               mean se_mean     sd   2.5%    25%    50%    75%  97.5%  n_eff   Rhat
mu            14.19  6.6e-3   0.31  13.58  13.98  14.19   14.4  14.81   2228    1.0
sigmaSq       31.82    0.05   2.43   27.5   30.1  31.69  33.37  36.82   2719    1.0
sigma          5.64  4.1e-3   0.21   5.24   5.49   5.63   5.78   6.07   2741    1.0
log_lik[0]    -3.71  1.9e-3   0.09   -3.9  -3.77  -3.71  -3.65  -3.54   2438    1.0
log_lik[1]    -2.66  7.4e-4   0.04  -2.74  -2.68  -2.66  -2.63  -2.59   2733    1.0
log_lik[2]     -2.7  7.6e-4   0.04  -2.78  -2.73   -2.7  -2.67  -2.63   2683    1.0
log_lik[3]    -2.66  7.4e-4   0.04  -2.74  -2.68  -2.66  -2.63  -2.59   2733    1.0
log_lik[4]    -3.01  1.0e-3   0.05  -3.11  -3.05  -3.01  -2.98  -2.92   2272    1.0
log_lik[5]    -2.77  8.1e-4   0.04  -2.86   -2.8  -2.77  -2.75   -2.7   2555    1.0
log_lik[6]    -2.77  8.1e-4   0.04  -2.86   -2.8  -2.77  -2.75   -2.7   2555    1.0
log_lik[7]    -2.77  8.1e-4   0.04  -2.86   -2.8  -2.77  -2.75   -2.7   2555    1.0
log_lik[8]    -3.98  2.3e-3   0.11  -4.22  -4.06  -3.98  -3.91  -3.78   2513    1.0
log_lik[9]    -2.77  8.1e-4   0.04  -2.86   -2.8  -2.77  -2.75   -2.7   2555    1.0
log_lik[10]   -2.77  8.1e-4   0.04  -2.86   -2.8  -2.77  -2.75   -2.7   2555    1.0
log_lik[11]   -3.08  1.1e-3   0.05  -3.18  -3.11  -3.07  -3.04  -2.98   2186    1.0
log_lik[12]   -3.71  1.9e-3   0.09   -3.9  -3.77  -3.71  -3.65  -3.54   2438    1.0
log_lik[13]   -2.77  8.1e-4   0.04  -2.86   -2.8  -2.77  -2.75   -2.7   2555    1.0
log_lik[14]   -3.98  2.3e-3   0.11  -4.22  -4.06  -3.98  -3.91  -3.78   2513    1.0
log_lik[15]   -3.71  1.9e-3   0.09   -3.9  -3.77  -3.71  -3.65  -3.54   2438    1.0
log_lik[16]   -2.81  8.7e-4   0.04  -2.89  -2.84  -2.81  -2.78  -2.74   2054    1.0
```

log_lik[17]	-3.08	1.1e-3	0.05	-3.18	-3.11	-3.07	-3.04	-2.98	2186	1.0
log_lik[18]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[19]	-3.38	1.5e-3	0.07	-3.52	-3.42	-3.38	-3.34	-3.25	2112	1.0
log_lik[20]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[21]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[22]	-4.17	2.6e-3	0.12	-4.41	-4.25	-4.16	-4.09	-3.95	2091	1.0
log_lik[23]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[24]	-3.08	1.1e-3	0.05	-3.18	-3.11	-3.07	-3.04	-2.98	2186	1.0
log_lik[25]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[26]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[27]	-2.73	8.1e-4	0.04	-2.8	-2.75	-2.72	-2.7	-2.65	2145	1.0
log_lik[28]	-3.01	1.0e-3	0.05	-3.11	-3.05	-3.01	-2.98	-2.92	2272	1.0
log_lik[29]	-3.08	1.1e-3	0.05	-3.18	-3.11	-3.07	-3.04	-2.98	2186	1.0
log_lik[30]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[31]	-2.73	8.1e-4	0.04	-2.8	-2.75	-2.72	-2.7	-2.65	2145	1.0
log_lik[32]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[33]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[34]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[35]	-4.5	3.1e-3	0.14	-4.79	-4.59	-4.49	-4.4	-4.23	2112	1.0
log_lik[36]	-3.01	1.0e-3	0.05	-3.11	-3.05	-3.01	-2.98	-2.92	2272	1.0
log_lik[37]	-4.17	2.6e-3	0.12	-4.41	-4.25	-4.16	-4.09	-3.95	2091	1.0
log_lik[38]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[39]	-3.98	2.3e-3	0.11	-4.22	-4.06	-3.98	-3.91	-3.78	2513	1.0
log_lik[40]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[41]	-3.18	1.2e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2205	1.0
log_lik[42]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[43]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[44]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[45]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[46]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[47]	-3.08	1.1e-3	0.05	-3.18	-3.11	-3.07	-3.04	-2.98	2186	1.0
log_lik[48]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[49]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[50]	-3.38	1.5e-3	0.07	-3.52	-3.42	-3.38	-3.34	-3.25	2112	1.0
log_lik[51]	-3.01	1.0e-3	0.05	-3.11	-3.05	-3.01	-2.98	-2.92	2272	1.0
log_lik[52]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[53]	-4.29	2.7e-3	0.14	-4.57	-4.38	-4.28	-4.2	-4.04	2574	1.0
log_lik[54]	-3.08	1.1e-3	0.05	-3.18	-3.11	-3.07	-3.04	-2.98	2186	1.0
log_lik[55]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[56]	-2.88	8.9e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2399	1.0
log_lik[57]	-2.73	8.1e-4	0.04	-2.8	-2.75	-2.72	-2.7	-2.65	2145	1.0
log_lik[58]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[59]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[60]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[61]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[62]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[63]	-3.47	1.6e-3	0.08	-3.62	-3.51	-3.46	-3.41	-3.33	2351	1.0
log_lik[64]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[65]	-3.18	1.2e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2205	1.0
log_lik[66]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[67]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[68]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[69]	-3.47	1.6e-3	0.08	-3.62	-3.51	-3.46	-3.41	-3.33	2351	1.0
log_lik[70]	-2.67	7.8e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	2296	1.0
log_lik[71]	-3.18	1.2e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2205	1.0
log_lik[72]	-3.18	1.2e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2205	1.0
log_lik[73]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[74]	-5.24	4.2e-3	0.2	-5.63	-5.37	-5.24	-5.11	-4.88	2161	1.0
log_lik[75]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[76]	-2.73	8.1e-4	0.04	-2.8	-2.75	-2.72	-2.7	-2.65	2145	1.0
log_lik[77]	-2.65	7.3e-4	0.04	-2.73	-2.67	-2.65	-2.62	-2.58	2690	1.0
log_lik[78]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[79]	-3.38	1.5e-3	0.07	-3.52	-3.42	-3.38	-3.34	-3.25	2112	1.0
log_lik[80]	-3.47	1.6e-3	0.08	-3.62	-3.51	-3.46	-3.41	-3.33	2351	1.0

log_lik[81]	-2.81	8.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.74	2054	1.0
log_lik[82]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[83]	-2.67	7.8e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	2296	1.0
log_lik[84]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[85]	-2.73	8.1e-4	0.04	-2.8	-2.75	-2.72	-2.7	-2.65	2145	1.0
log_lik[86]	-3.01	1.0e-3	0.05	-3.11	-3.05	-3.01	-2.98	-2.92	2272	1.0
log_lik[87]	-3.18	1.2e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2205	1.0
log_lik[88]	-2.88	8.9e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2399	1.0
log_lik[89]	-4.17	2.6e-3	0.12	-4.41	-4.25	-4.16	-4.09	-3.95	2091	1.0
log_lik[90]	-3.08	1.1e-3	0.05	-3.18	-3.11	-3.07	-3.04	-2.98	2186	1.0
log_lik[91]	-2.67	7.8e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	2296	1.0
log_lik[92]	-2.88	8.9e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2399	1.0
log_lik[93]	-3.38	1.5e-3	0.07	-3.52	-3.42	-3.38	-3.34	-3.25	2112	1.0
log_lik[94]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[95]	-2.65	7.3e-4	0.04	-2.73	-2.67	-2.65	-2.62	-2.58	2690	1.0
log_lik[96]	-3.08	1.1e-3	0.05	-3.18	-3.11	-3.07	-3.04	-2.98	2186	1.0
log_lik[97]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[98]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[99]	-4.63	3.2e-3	0.16	-4.96	-4.73	-4.62	-4.52	-4.33	2624	1.0
log_lik[100]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[101]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[102]	-3.18	1.2e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2205	1.0
log_lik[103]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[104]	-4.5	3.1e-3	0.14	-4.79	-4.59	-4.49	-4.4	-4.23	2112	1.0
log_lik[105]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[106]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[107]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[108]	-3.47	1.6e-3	0.08	-3.62	-3.51	-3.46	-3.41	-3.33	2351	1.0
log_lik[109]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[110]	-3.08	1.1e-3	0.05	-3.18	-3.11	-3.07	-3.04	-2.98	2186	1.0
log_lik[111]	-2.65	7.3e-4	0.04	-2.73	-2.67	-2.65	-2.62	-2.58	2690	1.0
log_lik[112]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[113]	-2.67	7.8e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	2296	1.0
log_lik[114]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[115]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[116]	-2.88	8.9e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2399	1.0
log_lik[117]	-4.5	3.1e-3	0.14	-4.79	-4.59	-4.49	-4.4	-4.23	2112	1.0
log_lik[118]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[119]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[120]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[121]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[122]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[123]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[124]	-2.81	8.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.74	2054	1.0
log_lik[125]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[126]	-2.88	8.9e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2399	1.0
log_lik[127]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[128]	-2.67	7.8e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	2296	1.0
log_lik[129]	-4.29	2.7e-3	0.14	-4.57	-4.38	-4.28	-4.2	-4.04	2574	1.0
log_lik[130]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[131]	-2.88	8.9e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2399	1.0
log_lik[132]	-3.18	1.2e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2205	1.0
log_lik[133]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[134]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[135]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[136]	-4.29	2.7e-3	0.14	-4.57	-4.38	-4.28	-4.2	-4.04	2574	1.0
log_lik[137]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[138]	-3.18	1.2e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2205	1.0
log_lik[139]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[140]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[141]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[142]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[143]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[144]	-3.98	2.3e-3	0.11	-4.22	-4.06	-3.98	-3.91	-3.78	2513	1.0

log_lik[145]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[146]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[147]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[148]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[149]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[150]	-2.81	8.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.74	2054	1.0
log_lik[151]	-3.08	1.1e-3	0.05	-3.18	-3.11	-3.07	-3.04	-2.98	2186	1.0
log_lik[152]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[153]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[154]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[155]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[156]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[157]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[158]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[159]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[160]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[161]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[162]	-3.88	2.2e-3	0.1	-4.08	-3.94	-3.87	-3.81	-3.69	2077	1.0
log_lik[163]	-3.01	1.0e-3	0.05	-3.11	-3.05	-3.01	-2.98	-2.92	2272	1.0
log_lik[164]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[165]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[166]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[167]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[168]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[169]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[170]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[171]	-4.85	3.6e-3	0.17	-5.19	-4.96	-4.85	-4.74	-4.54	2136	1.0
log_lik[172]	-2.67	7.8e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	2296	1.0
log_lik[173]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[174]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[175]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[176]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[177]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[178]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[179]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[180]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[181]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[182]	-2.81	8.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.74	2054	1.0
log_lik[183]	-3.88	2.2e-3	0.1	-4.08	-3.94	-3.87	-3.81	-3.69	2077	1.0
log_lik[184]	-3.18	1.2e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2205	1.0
log_lik[185]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[186]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[187]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[188]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[189]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[190]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[191]	-4.17	2.6e-3	0.12	-4.41	-4.25	-4.16	-4.09	-3.95	2091	1.0
log_lik[192]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[193]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[194]	-2.73	8.1e-4	0.04	-2.8	-2.75	-2.72	-2.7	-2.65	2145	1.0
log_lik[195]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[196]	-2.67	7.8e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	2296	1.0
log_lik[197]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[198]	-2.65	7.3e-4	0.04	-2.73	-2.67	-2.65	-2.62	-2.58	2690	1.0
log_lik[199]	-2.67	7.8e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	2296	1.0
log_lik[200]	-3.98	2.3e-3	0.11	-4.22	-4.06	-3.98	-3.91	-3.78	2513	1.0
log_lik[201]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[202]	-2.67	7.8e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	2296	1.0
log_lik[203]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[204]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[205]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[206]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[207]	-4.17	2.6e-3	0.12	-4.41	-4.25	-4.16	-4.09	-3.95	2091	1.0
log_lik[208]	-4.85	3.6e-3	0.17	-5.19	-4.96	-4.85	-4.74	-4.54	2136	1.0

log_lik[209]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[210]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[211]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[212]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[213]	-3.98	2.3e-3	0.11	-4.22	-4.06	-3.98	-3.91	-3.78	2513	1.0
log_lik[214]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[215]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[216]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[217]	-3.08	1.1e-3	0.05	-3.18	-3.11	-3.07	-3.04	-2.98	2186	1.0
log_lik[218]	-4.29	2.7e-3	0.14	-4.57	-4.38	-4.28	-4.2	-4.04	2574	1.0
log_lik[219]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[220]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[221]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[222]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[223]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[224]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[225]	-3.38	1.5e-3	0.07	-3.52	-3.42	-3.38	-3.34	-3.25	2112	1.0
log_lik[226]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[227]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[228]	-3.01	1.0e-3	0.05	-3.11	-3.05	-3.01	-2.98	-2.92	2272	1.0
log_lik[229]	-3.38	1.5e-3	0.07	-3.52	-3.42	-3.38	-3.34	-3.25	2112	1.0
log_lik[230]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[231]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[232]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[233]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[234]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[235]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[236]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[237]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[238]	-5.24	4.2e-3	0.2	-5.63	-5.37	-5.24	-5.11	-4.88	2161	1.0
log_lik[239]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[240]	-2.81	8.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.74	2054	1.0
log_lik[241]	-3.08	1.1e-3	0.05	-3.18	-3.11	-3.07	-3.04	-2.98	2186	1.0
log_lik[242]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[243]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[244]	-4.85	3.6e-3	0.17	-5.19	-4.96	-4.85	-4.74	-4.54	2136	1.0
log_lik[245]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[246]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[247]	-2.73	8.1e-4	0.04	-2.8	-2.75	-2.72	-2.7	-2.65	2145	1.0
log_lik[248]	-2.81	8.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.74	2054	1.0
log_lik[249]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[250]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[251]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[252]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[253]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[254]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[255]	-2.81	8.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.74	2054	1.0
log_lik[256]	-4.63	3.2e-3	0.16	-4.96	-4.73	-4.62	-4.52	-4.33	2624	1.0
log_lik[257]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[258]	-3.38	1.5e-3	0.07	-3.52	-3.42	-3.38	-3.34	-3.25	2112	1.0
log_lik[259]	-4.17	2.6e-3	0.12	-4.41	-4.25	-4.16	-4.09	-3.95	2091	1.0
log_lik[260]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[261]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[262]	-2.81	8.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.74	2054	1.0
log_lik[263]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[264]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[265]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[266]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[267]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[268]	-5.4	4.2e-3	0.22	-5.85	-5.55	-5.39	-5.25	-4.99	2694	1.0
log_lik[269]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[270]	-3.98	2.3e-3	0.11	-4.22	-4.06	-3.98	-3.91	-3.78	2513	1.0
log_lik[271]	-2.67	7.8e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	2296	1.0
log_lik[272]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0

log_lik[273]	-3.18	1.2e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2205	1.0
log_lik[274]	-3.18	1.2e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2205	1.0
log_lik[275]	-3.88	2.2e-3	0.1	-4.08	-3.94	-3.87	-3.81	-3.69	2077	1.0
log_lik[276]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[277]	-2.88	8.9e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2399	1.0
log_lik[278]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[279]	-4.29	2.7e-3	0.14	-4.57	-4.38	-4.28	-4.2	-4.04	2574	1.0
log_lik[280]	-2.81	8.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.74	2054	1.0
log_lik[281]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[282]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[283]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[284]	-3.18	1.2e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2205	1.0
log_lik[285]	-3.18	1.2e-3	0.06	-3.3	-3.22	-3.18	-3.14	-3.07	2205	1.0
log_lik[286]	-5.24	4.2e-3	0.2	-5.63	-5.37	-5.24	-5.11	-4.88	2161	1.0
log_lik[287]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[288]	-2.67	7.8e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	2296	1.0
log_lik[289]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[290]	-2.81	8.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.74	2054	1.0
log_lik[291]	-2.73	8.1e-4	0.04	-2.8	-2.75	-2.72	-2.7	-2.65	2145	1.0
log_lik[292]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[293]	-2.67	7.8e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	2296	1.0
log_lik[294]	-4.63	3.2e-3	0.16	-4.96	-4.73	-4.62	-4.52	-4.33	2624	1.0
log_lik[295]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[296]	-3.08	1.1e-3	0.05	-3.18	-3.11	-3.07	-3.04	-2.98	2186	1.0
log_lik[297]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[298]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[299]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[300]	-2.88	8.9e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2399	1.0
log_lik[301]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[302]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[303]	-4.29	2.7e-3	0.14	-4.57	-4.38	-4.28	-4.2	-4.04	2574	1.0
log_lik[304]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[305]	-2.67	7.8e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	2296	1.0
log_lik[306]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[307]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[308]	-2.88	8.9e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2399	1.0
log_lik[309]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[310]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[311]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[312]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[313]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[314]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[315]	-2.88	8.9e-4	0.04	-2.97	-2.91	-2.88	-2.85	-2.8	2399	1.0
log_lik[316]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[317]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[318]	-2.66	7.4e-4	0.04	-2.74	-2.68	-2.66	-2.63	-2.59	2733	1.0
log_lik[319]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[320]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[321]	-3.71	1.9e-3	0.09	-3.9	-3.77	-3.71	-3.65	-3.54	2438	1.0
log_lik[322]	-2.65	7.3e-4	0.04	-2.73	-2.67	-2.65	-2.62	-2.58	2690	1.0
log_lik[323]	-2.81	8.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.74	2054	1.0
log_lik[324]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[325]	-2.73	8.1e-4	0.04	-2.8	-2.75	-2.72	-2.7	-2.65	2145	1.0
log_lik[326]	-3.26	1.3e-3	0.06	-3.38	-3.29	-3.25	-3.21	-3.14	2263	1.0
log_lik[327]	-2.93	9.6e-4	0.04	-3.02	-2.95	-2.93	-2.9	-2.85	2055	1.0
log_lik[328]	-2.77	8.1e-4	0.04	-2.86	-2.8	-2.77	-2.75	-2.7	2555	1.0
log_lik[329]	-4.85	3.6e-3	0.17	-5.19	-4.96	-4.85	-4.74	-4.54	2136	1.0
log_lik[330]	-3.38	1.5e-3	0.07	-3.52	-3.42	-3.38	-3.34	-3.25	2112	1.0
log_lik[331]	-3.61	1.8e-3	0.08	-3.77	-3.67	-3.61	-3.56	-3.46	2080	1.0
log_lik[332]	-2.7	7.6e-4	0.04	-2.78	-2.73	-2.7	-2.67	-2.63	2683	1.0
log_lik[333]	-2.81	8.7e-4	0.04	-2.89	-2.84	-2.81	-2.78	-2.74	2054	1.0
log_lik[334]	-3.47	1.6e-3	0.08	-3.62	-3.51	-3.46	-3.41	-3.33	2351	1.0
ypred	14.26	0.09	5.61	3.24	10.48	14.33	18.0	25.22	3898	1.0
lp__	-751.2	0.03	1.01	-753.9	-751.5	-750.9	-750.4	-750.2	1496	1.0

```
Samples were drawn using NUTS at Sun Dec  9 13:47:30 2018.
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).

##########################################################################
####### Attachment 3: Fit of hierarchical model with uniform prior #######
##########################################################################

Inference for Stan model: anon_model_c4c17a1f535ecd44756a69898a3750cd.
4 chains, each with iter=2000; warmup=1000; thin=1;
post-warmup draws per chain=1000, total post-warmup draws=4000.

                mean se_mean     sd   2.5%    25%    50%    75%  97.5%  n_eff   Rhat
mu0             14.2    0.01   0.46  13.25  13.92  14.19  14.46   15.1   1045    1.0
sigma0          0.55    0.02   0.58   0.01   0.18   0.39   0.72   2.06   1027    1.0
sigma           5.67  3.4e-3   0.21   5.27   5.52   5.66   5.81   6.11   4000    1.0
mu_tilde[0]    -0.21    0.02   0.88  -1.97   -0.8  -0.22   0.37   1.49   3064    1.0
mu_tilde[1]     0.11    0.02   0.88  -1.68  -0.48    0.1   0.69   1.88   3285    1.0
mu_tilde[2]    -0.21    0.02   0.88  -1.89   -0.8  -0.22   0.37   1.52   2993    1.0
mu_tilde[3]     0.33    0.02   0.85  -1.43   -0.2   0.35    0.9   1.95   2605    1.0
mu_tilde[4]    -0.03    0.01   0.86  -1.74   -0.6  -0.02   0.53   1.71   3305    1.0
mu[0]          14.06  7.6e-3   0.48  12.98  13.79  14.09  14.37  14.95   4000    1.0
mu[1]          14.25  7.4e-3   0.47  13.31  13.95  14.25  14.55  15.23   4000    1.0
mu[2]          14.06  7.6e-3   0.48  13.03  13.77  14.08  14.38  14.95   4000    1.0
mu[3]          14.41  7.8e-3    0.5  13.54  14.06  14.36   14.7   15.5   4000    1.0
mu[4]          14.18  7.5e-3   0.47  13.22  13.89  14.19  14.47  15.12   4000    1.0
log_lik[0,0]   -3.67  2.0e-3   0.13  -3.91  -3.75  -3.67   -3.6  -3.41   4000    1.0
log_lik[1,0]   -2.67  6.3e-4   0.04  -2.75   -2.7  -2.67  -2.64   -2.6   4000    1.0
log_lik[2,0]   -2.72  7.2e-4   0.05  -2.81  -2.74  -2.71  -2.69  -2.63   4000    1.0
log_lik[3,0]   -2.67  6.3e-4   0.04  -2.75   -2.7  -2.67  -2.64   -2.6   4000    1.0
log_lik[4,0]   -3.04  1.2e-3   0.08  -3.22  -3.08  -3.03  -2.99  -2.91   4000    1.0
log_lik[5,0]   -2.79  8.5e-4   0.05  -2.92  -2.82  -2.79  -2.76   -2.7   4000    1.0
log_lik[6,0]   -2.79  8.5e-4   0.05  -2.92  -2.82  -2.79  -2.76   -2.7   4000    1.0
log_lik[7,0]   -2.79  8.5e-4   0.05  -2.92  -2.82  -2.79  -2.76   -2.7   4000    1.0
log_lik[8,0]   -3.94  2.3e-3   0.15  -4.22  -4.03  -3.94  -3.85  -3.63   4000    1.0
log_lik[9,0]   -2.79  8.5e-4   0.05  -2.92  -2.82  -2.79  -2.76   -2.7   4000    1.0
log_lik[10,0]  -2.79  8.5e-4   0.05  -2.92  -2.82  -2.79  -2.76   -2.7   4000    1.0
log_lik[11,0]  -3.06  1.2e-3   0.08  -3.21   -3.1  -3.06  -3.01   -2.9   4000    1.0
log_lik[12,0]  -3.67  2.0e-3   0.13  -3.91  -3.75  -3.67   -3.6  -3.41   4000    1.0
log_lik[13,0]  -2.79  8.5e-4   0.05  -2.92  -2.82  -2.79  -2.76   -2.7   4000    1.0
log_lik[14,0]  -3.94  2.3e-3   0.15  -4.22  -4.03  -3.94  -3.85  -3.63   4000    1.0
log_lik[15,0]  -3.67  2.0e-3   0.13  -3.91  -3.75  -3.67   -3.6  -3.41   4000    1.0
log_lik[16,0]   -2.8  8.2e-4   0.05  -2.91  -2.84   -2.8  -2.77   -2.7   4000    1.0
log_lik[17,0]  -3.06  1.2e-3   0.08  -3.21   -3.1  -3.06  -3.01   -2.9   4000    1.0
log_lik[18,0]  -2.72  7.2e-4   0.05  -2.81  -2.74  -2.71  -2.69  -2.63   4000    1.0
log_lik[19,0]  -3.41  1.7e-3   0.11  -3.66  -3.47   -3.4  -3.34  -3.22   4000    1.0
log_lik[20,0]  -2.79  8.5e-4   0.05  -2.92  -2.82  -2.79  -2.76   -2.7   4000    1.0
log_lik[21,0]  -2.67  6.3e-4   0.04  -2.75   -2.7  -2.67  -2.64   -2.6   4000    1.0
log_lik[22,0]   -4.2  2.7e-3   0.17  -4.59   -4.3  -4.19  -4.09   -3.9   4000    1.0
log_lik[23,0]  -2.91  9.9e-4   0.06  -3.04  -2.95  -2.92  -2.88  -2.78   4000    1.0
log_lik[24,0]  -3.06  1.2e-3   0.08  -3.21   -3.1  -3.06  -3.01   -2.9   4000    1.0
log_lik[25,0]  -3.23  1.4e-3   0.09  -3.41  -3.29  -3.23  -3.18  -3.04   4000    1.0
log_lik[26,0]  -3.64  2.0e-3   0.13  -3.93  -3.71  -3.63  -3.56  -3.42   4000    1.0
log_lik[27,0]  -2.72  7.0e-4   0.04  -2.81  -2.75  -2.72  -2.69  -2.64   4000    1.0
log_lik[28,0]  -3.04  1.2e-3   0.08  -3.22  -3.08  -3.03  -2.99  -2.91   4000    1.0
log_lik[29,0]  -3.06  1.2e-3   0.08  -3.21   -3.1  -3.06  -3.01   -2.9   4000    1.0
log_lik[30,0]  -2.67  6.3e-4   0.04  -2.75   -2.7  -2.67  -2.64   -2.6   4000    1.0
log_lik[31,0]  -2.72  7.0e-4   0.04  -2.81  -2.75  -2.72  -2.69  -2.64   4000    1.0
log_lik[32,0]  -3.23  1.4e-3   0.09  -3.41  -3.29  -3.23  -3.18  -3.04   4000    1.0
log_lik[33,0]  -2.79  8.5e-4   0.05  -2.92  -2.82  -2.79  -2.76   -2.7   4000    1.0
log_lik[34,0]  -2.67  6.3e-4   0.04  -2.75   -2.7  -2.67  -2.64   -2.6   4000    1.0
log_lik[35,0]  -4.53  3.1e-3   0.19  -4.96  -4.64  -4.51   -4.4  -4.18   4000    1.0
```

log_lik[36,0]	-3.04	1.2e-3	0.08	-3.22	-3.08	-3.03	-2.99	-2.91	4000	1.0
log_lik[37,0]	-4.2	2.7e-3	0.17	-4.59	-4.3	-4.19	-4.09	-3.9	4000	1.0
log_lik[38,0]	-2.72	7.2e-4	0.05	-2.81	-2.74	-2.71	-2.69	-2.63	4000	1.0
log_lik[39,0]	-3.94	2.3e-3	0.15	-4.22	-4.03	-3.94	-3.85	-3.63	4000	1.0
log_lik[40,0]	-2.79	8.5e-4	0.05	-2.92	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[41,0]	-3.21	1.4e-3	0.09	-3.42	-3.26	-3.2	-3.15	-3.05	4000	1.0
log_lik[42,0]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.18	-3.04	4000	1.0
log_lik[43,0]	-3.64	2.0e-3	0.13	-3.93	-3.71	-3.63	-3.56	-3.42	4000	1.0
log_lik[44,0]	-2.67	6.3e-4	0.04	-2.75	-2.7	-2.67	-2.64	-2.6	4000	1.0
log_lik[45,0]	-3.67	2.0e-3	0.13	-3.91	-3.75	-3.67	-3.6	-3.41	4000	1.0
log_lik[46,0]	-3.67	2.0e-3	0.13	-3.91	-3.75	-3.67	-3.6	-3.41	4000	1.0
log_lik[47,0]	-3.06	1.2e-3	0.08	-3.21	-3.1	-3.06	-3.01	-2.9	4000	1.0
log_lik[48,0]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.18	-3.04	4000	1.0
log_lik[49,0]	-2.79	8.5e-4	0.05	-2.92	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[50,0]	-3.41	1.7e-3	0.11	-3.66	-3.47	-3.4	-3.34	-3.22	4000	1.0
log_lik[51,0]	-3.04	1.2e-3	0.08	-3.22	-3.08	-3.03	-2.99	-2.91	4000	1.0
log_lik[52,0]	-3.64	2.0e-3	0.13	-3.93	-3.71	-3.63	-3.56	-3.42	4000	1.0
log_lik[53,0]	-4.24	2.7e-3	0.17	-4.56	-4.35	-4.24	-4.13	-3.88	4000	1.0
log_lik[54,0]	-3.06	1.2e-3	0.08	-3.21	-3.1	-3.06	-3.01	-2.9	4000	1.0
log_lik[55,0]	-2.72	7.2e-4	0.05	-2.81	-2.74	-2.71	-2.69	-2.63	4000	1.0
log_lik[56,0]	-2.9	1.0e-3	0.06	-3.05	-2.93	-2.89	-2.86	-2.79	4000	1.0
log_lik[57,0]	-2.72	7.0e-4	0.04	-2.81	-2.75	-2.72	-2.69	-2.64	4000	1.0
log_lik[58,0]	-2.67	6.3e-4	0.04	-2.75	-2.7	-2.67	-2.64	-2.6	4000	1.0
log_lik[59,0]	-2.91	9.9e-4	0.06	-3.04	-2.95	-2.92	-2.88	-2.78	4000	1.0
log_lik[60,0]	-3.67	2.0e-3	0.13	-3.91	-3.75	-3.67	-3.6	-3.41	4000	1.0
log_lik[61,0]	-2.91	9.9e-4	0.06	-3.04	-2.95	-2.92	-2.88	-2.78	4000	1.0
log_lik[62,0]	-3.67	2.0e-3	0.13	-3.91	-3.75	-3.67	-3.6	-3.41	4000	1.0
log_lik[63,0]	-3.44	1.7e-3	0.11	-3.64	-3.5	-3.44	-3.37	-3.21	4000	1.0
log_lik[64,0]	-2.72	7.2e-4	0.05	-2.81	-2.74	-2.71	-2.69	-2.63	4000	1.0
log_lik[65,0]	-3.21	1.4e-3	0.09	-3.42	-3.26	-3.2	-3.15	-3.05	4000	1.0
log_lik[66,0]	-3.64	2.0e-3	0.13	-3.93	-3.71	-3.63	-3.56	-3.42	4000	1.0
log_lik[0,1]	-2.77	7.9e-4	0.05	-2.88	-2.81	-2.77	-2.74	-2.68	4000	1.0
log_lik[1,1]	-2.67	6.2e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	4000	1.0
log_lik[2,1]	-3.48	1.7e-3	0.11	-3.72	-3.54	-3.47	-3.41	-3.27	4000	1.0
log_lik[3,1]	-2.68	6.4e-4	0.04	-2.76	-2.71	-2.68	-2.65	-2.6	4000	1.0
log_lik[4,1]	-3.17	1.3e-3	0.08	-3.35	-3.23	-3.17	-3.12	-3.01	4000	1.0
log_lik[5,1]	-3.17	1.3e-3	0.08	-3.35	-3.23	-3.17	-3.12	-3.01	4000	1.0
log_lik[6,1]	-2.7	6.8e-4	0.04	-2.79	-2.73	-2.7	-2.67	-2.62	4000	1.0
log_lik[7,1]	-5.2	3.7e-3	0.24	-5.68	-5.35	-5.19	-5.04	-4.74	4000	1.0
log_lik[8,1]	-2.77	7.9e-4	0.05	-2.88	-2.81	-2.77	-2.74	-2.68	4000	1.0
log_lik[9,1]	-2.74	7.2e-4	0.05	-2.83	-2.76	-2.73	-2.7	-2.65	4000	1.0
log_lik[10,1]	-2.66	6.0e-4	0.04	-2.73	-2.68	-2.66	-2.63	-2.58	4000	1.0
log_lik[11,1]	-2.77	7.9e-4	0.05	-2.88	-2.81	-2.77	-2.74	-2.68	4000	1.0
log_lik[12,1]	-3.37	1.6e-3	0.1	-3.57	-3.43	-3.36	-3.3	-3.18	4000	1.0
log_lik[13,1]	-3.48	1.7e-3	0.11	-3.72	-3.54	-3.47	-3.41	-3.27	4000	1.0
log_lik[14,1]	-2.82	8.4e-4	0.05	-2.94	-2.85	-2.82	-2.78	-2.73	4000	1.0
log_lik[15,1]	-3.72	2.0e-3	0.13	-3.99	-3.8	-3.72	-3.63	-3.48	4000	1.0
log_lik[16,1]	-2.68	6.4e-4	0.04	-2.76	-2.71	-2.68	-2.65	-2.6	4000	1.0
log_lik[17,1]	-3.27	1.5e-3	0.09	-3.47	-3.32	-3.26	-3.21	-3.1	4000	1.0
log_lik[18,1]	-2.74	7.2e-4	0.05	-2.83	-2.76	-2.73	-2.7	-2.65	4000	1.0
log_lik[19,1]	-3.01	1.1e-3	0.07	-3.16	-3.05	-3.01	-2.96	-2.88	4000	1.0
log_lik[20,1]	-3.17	1.3e-3	0.08	-3.35	-3.23	-3.17	-3.12	-3.01	4000	1.0
log_lik[21,1]	-2.88	9.3e-4	0.06	-3.0	-2.91	-2.87	-2.84	-2.77	4000	1.0
log_lik[22,1]	-4.14	2.5e-3	0.16	-4.46	-4.24	-4.14	-4.04	-3.84	4000	1.0
log_lik[23,1]	-3.09	1.2e-3	0.08	-3.26	-3.13	-3.08	-3.04	-2.95	4000	1.0
log_lik[24,1]	-2.68	6.4e-4	0.04	-2.76	-2.71	-2.68	-2.65	-2.6	4000	1.0
log_lik[25,1]	-2.88	9.3e-4	0.06	-3.0	-2.91	-2.87	-2.84	-2.77	4000	1.0
log_lik[26,1]	-3.37	1.6e-3	0.1	-3.57	-3.43	-3.36	-3.3	-3.18	4000	1.0
log_lik[27,1]	-2.67	6.2e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	4000	1.0
log_lik[28,1]	-2.66	6.0e-4	0.04	-2.73	-2.68	-2.66	-2.63	-2.58	4000	1.0
log_lik[29,1]	-3.09	1.2e-3	0.08	-3.26	-3.13	-3.08	-3.04	-2.95	4000	1.0
log_lik[30,1]	-3.72	2.0e-3	0.13	-3.99	-3.8	-3.72	-3.63	-3.48	4000	1.0
log_lik[31,1]	-2.77	7.9e-4	0.05	-2.88	-2.81	-2.77	-2.74	-2.68	4000	1.0
log_lik[32,1]	-4.64	3.2e-3	0.2	-5.05	-4.76	-4.63	-4.5	-4.26	4000	1.0

log_lik[33,1]	-2.67	6.2e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	4000	1.0
log_lik[34,1]	-2.7	6.8e-4	0.04	-2.79	-2.73	-2.7	-2.67	-2.62	4000	1.0
log_lik[35,1]	-3.17	1.3e-3	0.08	-3.35	-3.23	-3.17	-3.12	-3.01	4000	1.0
log_lik[36,1]	-2.77	7.9e-4	0.05	-2.88	-2.81	-2.77	-2.74	-2.68	4000	1.0
log_lik[37,1]	-4.46	2.9e-3	0.18	-4.83	-4.58	-4.46	-4.34	-4.11	4000	1.0
log_lik[38,1]	-3.72	2.0e-3	0.13	-3.99	-3.8	-3.72	-3.63	-3.48	4000	1.0
log_lik[39,1]	-2.77	7.9e-4	0.05	-2.88	-2.81	-2.77	-2.74	-2.68	4000	1.0
log_lik[40,1]	-2.7	6.8e-4	0.04	-2.79	-2.73	-2.7	-2.67	-2.62	4000	1.0
log_lik[41,1]	-3.48	1.7e-3	0.11	-3.72	-3.54	-3.47	-3.41	-3.27	4000	1.0
log_lik[42,1]	-3.72	2.0e-3	0.13	-3.99	-3.8	-3.72	-3.63	-3.48	4000	1.0
log_lik[43,1]	-3.09	1.2e-3	0.08	-3.26	-3.13	-3.08	-3.04	-2.95	4000	1.0
log_lik[44,1]	-2.66	6.0e-4	0.04	-2.73	-2.68	-2.66	-2.63	-2.58	4000	1.0
log_lik[45,1]	-3.72	2.0e-3	0.13	-3.99	-3.8	-3.72	-3.63	-3.48	4000	1.0
log_lik[46,1]	-2.68	6.4e-4	0.04	-2.76	-2.71	-2.68	-2.65	-2.6	4000	1.0
log_lik[47,1]	-3.27	1.5e-3	0.09	-3.47	-3.32	-3.26	-3.21	-3.1	4000	1.0
log_lik[48,1]	-2.94	1.0e-3	0.06	-3.08	-2.98	-2.94	-2.89	-2.82	4000	1.0
log_lik[49,1]	-2.88	9.3e-4	0.06	-3.0	-2.91	-2.87	-2.84	-2.77	4000	1.0
log_lik[50,1]	-4.46	2.9e-3	0.18	-4.83	-4.58	-4.46	-4.34	-4.11	4000	1.0
log_lik[51,1]	-2.77	7.9e-4	0.05	-2.88	-2.81	-2.77	-2.74	-2.68	4000	1.0
log_lik[52,1]	-3.59	1.8e-3	0.12	-3.83	-3.67	-3.59	-3.52	-3.37	4000	1.0
log_lik[53,1]	-2.94	1.0e-3	0.06	-3.08	-2.98	-2.94	-2.89	-2.82	4000	1.0
log_lik[54,1]	-2.67	6.2e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	4000	1.0
log_lik[55,1]	-3.72	2.0e-3	0.13	-3.99	-3.8	-3.72	-3.63	-3.48	4000	1.0
log_lik[56,1]	-2.77	7.9e-4	0.05	-2.88	-2.81	-2.77	-2.74	-2.68	4000	1.0
log_lik[57,1]	-2.82	8.4e-4	0.05	-2.94	-2.85	-2.82	-2.78	-2.73	4000	1.0
log_lik[58,1]	-3.59	1.8e-3	0.12	-3.83	-3.67	-3.59	-3.52	-3.37	4000	1.0
log_lik[59,1]	-2.88	9.3e-4	0.06	-3.0	-2.91	-2.87	-2.84	-2.77	4000	1.0
log_lik[60,1]	-2.77	7.9e-4	0.05	-2.88	-2.81	-2.77	-2.74	-2.68	4000	1.0
log_lik[61,1]	-2.68	6.4e-4	0.04	-2.76	-2.71	-2.68	-2.65	-2.6	4000	1.0
log_lik[62,1]	-4.3	2.8e-3	0.17	-4.66	-4.41	-4.29	-4.18	-3.98	4000	1.0
log_lik[63,1]	-2.94	1.0e-3	0.06	-3.08	-2.98	-2.94	-2.89	-2.82	4000	1.0
log_lik[64,1]	-2.88	9.3e-4	0.06	-3.0	-2.91	-2.87	-2.84	-2.77	4000	1.0
log_lik[65,1]	-3.17	1.3e-3	0.08	-3.35	-3.23	-3.17	-3.12	-3.01	4000	1.0
log_lik[66,1]	-2.77	7.9e-4	0.05	-2.88	-2.81	-2.77	-2.74	-2.68	4000	1.0
log_lik[0,2]	-2.72	7.1e-4	0.05	-2.81	-2.74	-2.71	-2.69	-2.63	4000	1.0
log_lik[1,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[2,2]	-4.24	2.7e-3	0.17	-4.58	-4.35	-4.23	-4.13	-3.9	4000	1.0
log_lik[3,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[4,2]	-3.21	1.4e-3	0.09	-3.41	-3.26	-3.2	-3.15	-3.05	4000	1.0
log_lik[5,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[6,2]	-2.67	6.3e-4	0.04	-2.75	-2.7	-2.67	-2.64	-2.59	4000	1.0
log_lik[7,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[8,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[9,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[10,2]	-3.94	2.3e-3	0.15	-4.24	-4.04	-3.94	-3.85	-3.65	4000	1.0
log_lik[11,2]	-2.72	7.1e-4	0.05	-2.81	-2.74	-2.71	-2.69	-2.63	4000	1.0
log_lik[12,2]	-2.72	7.1e-4	0.05	-2.81	-2.74	-2.71	-2.69	-2.63	4000	1.0
log_lik[13,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[14,2]	-2.72	7.1e-4	0.05	-2.81	-2.74	-2.71	-2.69	-2.63	4000	1.0
log_lik[15,2]	-3.67	2.0e-3	0.13	-3.92	-3.75	-3.67	-3.59	-3.42	4000	1.0
log_lik[16,2]	-2.8	8.3e-4	0.05	-2.91	-2.84	-2.8	-2.77	-2.7	4000	1.0
log_lik[17,2]	-3.06	1.2e-3	0.08	-3.21	-3.11	-3.06	-3.01	-2.91	4000	1.0
log_lik[18,2]	-2.91	9.9e-4	0.06	-3.04	-2.96	-2.92	-2.87	-2.79	4000	1.0
log_lik[19,2]	-2.67	6.3e-4	0.04	-2.75	-2.7	-2.67	-2.64	-2.59	4000	1.0
log_lik[20,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[21,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[22,2]	-3.64	2.0e-3	0.13	-3.91	-3.72	-3.63	-3.56	-3.43	4000	1.0
log_lik[23,2]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.17	-3.05	4000	1.0
log_lik[24,2]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.17	-3.05	4000	1.0
log_lik[25,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[26,2]	-3.64	2.0e-3	0.13	-3.91	-3.72	-3.63	-3.56	-3.43	4000	1.0
log_lik[27,2]	-2.67	6.3e-4	0.04	-2.75	-2.7	-2.67	-2.64	-2.59	4000	1.0
log_lik[28,2]	-3.91	2.3e-3	0.15	-4.22	-3.99	-3.89	-3.81	-3.65	4000	1.0
log_lik[29,2]	-3.04	1.2e-3	0.08	-3.21	-3.08	-3.03	-2.99	-2.91	4000	1.0

log_lik[30,2]	-3.67	2.0e-3	0.13	-3.92	-3.75	-3.67	-3.59	-3.42	4000	1.0
log_lik[31,2]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.17	-3.05	4000	1.0
log_lik[32,2]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.17	-3.05	4000	1.0
log_lik[33,2]	-3.67	2.0e-3	0.13	-3.92	-3.75	-3.67	-3.59	-3.42	4000	1.0
log_lik[34,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[35,2]	-2.67	6.3e-4	0.04	-2.75	-2.7	-2.67	-2.64	-2.59	4000	1.0
log_lik[36,2]	-2.67	6.3e-4	0.04	-2.75	-2.7	-2.67	-2.64	-2.59	4000	1.0
log_lik[37,2]	-4.88	3.5e-3	0.22	-5.36	-5.02	-4.87	-4.73	-4.49	4000	1.0
log_lik[38,2]	-2.67	6.2e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	4000	1.0
log_lik[39,2]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.17	-3.05	4000	1.0
log_lik[40,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[41,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[42,2]	-2.67	6.3e-4	0.04	-2.75	-2.7	-2.67	-2.64	-2.59	4000	1.0
log_lik[43,2]	-2.67	6.3e-4	0.04	-2.75	-2.7	-2.67	-2.64	-2.59	4000	1.0
log_lik[44,2]	-3.67	2.0e-3	0.13	-3.92	-3.75	-3.67	-3.59	-3.42	4000	1.0
log_lik[45,2]	-3.67	2.0e-3	0.13	-3.92	-3.75	-3.67	-3.59	-3.42	4000	1.0
log_lik[46,2]	-2.91	9.9e-4	0.06	-3.04	-2.96	-2.92	-2.87	-2.79	4000	1.0
log_lik[47,2]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.17	-3.05	4000	1.0
log_lik[48,2]	-2.8	8.3e-4	0.05	-2.91	-2.84	-2.8	-2.77	-2.7	4000	1.0
log_lik[49,2]	-3.91	2.3e-3	0.15	-4.22	-3.99	-3.89	-3.81	-3.65	4000	1.0
log_lik[50,2]	-3.21	1.4e-3	0.09	-3.41	-3.26	-3.2	-3.15	-3.05	4000	1.0
log_lik[51,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[52,2]	-3.67	2.0e-3	0.13	-3.92	-3.75	-3.67	-3.59	-3.42	4000	1.0
log_lik[53,2]	-2.91	9.9e-4	0.06	-3.04	-2.96	-2.92	-2.87	-2.79	4000	1.0
log_lik[54,2]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.17	-3.05	4000	1.0
log_lik[55,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[56,2]	-2.72	7.1e-4	0.05	-2.81	-2.74	-2.71	-2.69	-2.63	4000	1.0
log_lik[57,2]	-4.2	2.7e-3	0.17	-4.57	-4.31	-4.18	-4.09	-3.91	4000	1.0
log_lik[58,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[59,2]	-2.79	8.4e-4	0.05	-2.91	-2.82	-2.79	-2.76	-2.7	4000	1.0
log_lik[60,2]	-2.72	7.0e-4	0.04	-2.81	-2.75	-2.72	-2.69	-2.64	4000	1.0
log_lik[61,2]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.17	-3.05	4000	1.0
log_lik[62,2]	-2.67	6.2e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	4000	1.0
log_lik[63,2]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.17	-3.05	4000	1.0
log_lik[64,2]	-2.66	6.0e-4	0.04	-2.73	-2.68	-2.66	-2.63	-2.58	4000	1.0
log_lik[65,2]	-2.67	6.2e-4	0.04	-2.75	-2.7	-2.67	-2.65	-2.6	4000	1.0
log_lik[66,2]	-3.94	2.3e-3	0.15	-4.24	-4.04	-3.94	-3.85	-3.65	4000	1.0
log_lik[0,3]	-3.76	2.2e-3	0.14	-4.09	-3.84	-3.75	-3.66	-3.53	4000	1.0
log_lik[1,3]	-2.69	6.7e-4	0.04	-2.78	-2.72	-2.69	-2.66	-2.61	4000	1.0
log_lik[2,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[3,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[4,3]	-2.66	6.1e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	4000	1.0
log_lik[5,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[6,3]	-4.09	2.5e-3	0.16	-4.4	-4.2	-4.1	-3.99	-3.77	4000	1.0
log_lik[7,3]	-4.76	3.3e-3	0.21	-5.16	-4.9	-4.76	-4.62	-4.34	4000	1.0
log_lik[8,3]	-2.96	1.1e-3	0.07	-3.13	-3.0	-2.95	-2.91	-2.85	4000	1.0
log_lik[9,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[10,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[11,3]	-2.7	6.7e-4	0.04	-2.78	-2.72	-2.7	-2.67	-2.61	4000	1.0
log_lik[12,3]	-4.04	2.6e-3	0.16	-4.41	-4.13	-4.02	-3.93	-3.77	4000	1.0
log_lik[13,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[14,3]	-3.76	2.2e-3	0.14	-4.09	-3.84	-3.75	-3.66	-3.53	4000	1.0
log_lik[15,3]	-2.66	6.1e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	4000	1.0
log_lik[16,3]	-3.11	1.4e-3	0.09	-3.31	-3.16	-3.1	-3.05	-2.98	4000	1.0
log_lik[17,3]	-4.35	3.0e-3	0.19	-4.77	-4.46	-4.33	-4.22	-4.03	4000	1.0
log_lik[18,3]	-2.96	1.1e-3	0.07	-3.13	-3.0	-2.95	-2.91	-2.85	4000	1.0
log_lik[19,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[20,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[21,3]	-2.66	6.1e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	4000	1.0
log_lik[22,3]	-3.56	1.9e-3	0.12	-3.78	-3.64	-3.56	-3.48	-3.31	4000	1.0
log_lik[23,3]	-2.7	6.7e-4	0.04	-2.78	-2.72	-2.7	-2.67	-2.61	4000	1.0
log_lik[24,3]	-3.34	1.6e-3	0.1	-3.52	-3.4	-3.34	-3.27	-3.13	4000	1.0
log_lik[25,3]	-2.96	1.1e-3	0.07	-3.13	-3.0	-2.95	-2.91	-2.85	4000	1.0
log_lik[26,3]	-3.56	1.9e-3	0.12	-3.78	-3.64	-3.56	-3.48	-3.31	4000	1.0

log_lik[27,3]	-2.99	1.1e-3	0.07	-3.12	-3.03	-2.99	-2.94	-2.84	4000	1.0
log_lik[28,3]	-3.34	1.6e-3	0.1	-3.52	-3.4	-3.34	-3.27	-3.13	4000	1.0
log_lik[29,3]	-2.66	6.1e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	4000	1.0
log_lik[30,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[31,3]	-2.7	6.7e-4	0.04	-2.78	-2.72	-2.7	-2.67	-2.61	4000	1.0
log_lik[32,3]	-3.3	1.6e-3	0.1	-3.53	-3.35	-3.29	-3.23	-3.13	4000	1.0
log_lik[33,3]	-2.96	1.1e-3	0.07	-3.13	-3.0	-2.95	-2.91	-2.85	4000	1.0
log_lik[34,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[35,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[36,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[37,3]	-5.13	3.8e-3	0.24	-5.6	-5.3	-5.14	-4.98	-4.67	4000	1.0
log_lik[38,3]	-3.76	2.2e-3	0.14	-4.09	-3.84	-3.75	-3.66	-3.53	4000	1.0
log_lik[39,3]	-2.84	9.4e-4	0.06	-2.98	-2.87	-2.83	-2.8	-2.74	4000	1.0
log_lik[40,3]	-3.11	1.4e-3	0.09	-3.31	-3.16	-3.1	-3.05	-2.98	4000	1.0
log_lik[41,3]	-2.96	1.1e-3	0.07	-3.13	-3.0	-2.95	-2.91	-2.85	4000	1.0
log_lik[42,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[43,3]	-4.76	3.3e-3	0.21	-5.16	-4.9	-4.76	-4.62	-4.34	4000	1.0
log_lik[44,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[45,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[46,3]	-2.75	7.8e-4	0.05	-2.86	-2.78	-2.74	-2.71	-2.66	4000	1.0
log_lik[47,3]	-2.84	9.4e-4	0.06	-2.98	-2.87	-2.83	-2.8	-2.74	4000	1.0
log_lik[48,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[49,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[50,3]	-3.3	1.6e-3	0.1	-3.53	-3.35	-3.29	-3.23	-3.13	4000	1.0
log_lik[51,3]	-2.7	6.7e-4	0.04	-2.78	-2.72	-2.7	-2.67	-2.61	4000	1.0
log_lik[52,3]	-3.3	1.6e-3	0.1	-3.53	-3.35	-3.29	-3.23	-3.13	4000	1.0
log_lik[53,3]	-3.76	2.2e-3	0.14	-4.09	-3.84	-3.75	-3.66	-3.53	4000	1.0
log_lik[54,3]	-2.84	9.4e-4	0.06	-2.98	-2.87	-2.83	-2.8	-2.74	4000	1.0
log_lik[55,3]	-4.69	3.4e-3	0.22	-5.18	-4.82	-4.67	-4.54	-4.32	4000	1.0
log_lik[56,3]	-3.3	1.6e-3	0.1	-3.53	-3.35	-3.29	-3.23	-3.13	4000	1.0
log_lik[57,3]	-3.34	1.6e-3	0.1	-3.52	-3.4	-3.34	-3.27	-3.13	4000	1.0
log_lik[58,3]	-4.09	2.5e-3	0.16	-4.4	-4.2	-4.1	-3.99	-3.77	4000	1.0
log_lik[59,3]	-3.56	1.9e-3	0.12	-3.78	-3.64	-3.56	-3.48	-3.31	4000	1.0
log_lik[60,3]	-3.56	1.9e-3	0.12	-3.78	-3.64	-3.56	-3.48	-3.31	4000	1.0
log_lik[61,3]	-2.84	9.4e-4	0.06	-2.98	-2.87	-2.83	-2.8	-2.74	4000	1.0
log_lik[62,3]	-2.76	7.8e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[63,3]	-2.66	6.1e-4	0.04	-2.74	-2.69	-2.66	-2.64	-2.59	4000	1.0
log_lik[64,3]	-3.56	1.9e-3	0.12	-3.78	-3.64	-3.56	-3.48	-3.31	4000	1.0
log_lik[65,3]	-3.76	2.2e-3	0.14	-4.09	-3.84	-3.75	-3.66	-3.53	4000	1.0
log_lik[66,3]	-3.56	1.9e-3	0.12	-3.78	-3.64	-3.56	-3.48	-3.31	4000	1.0
log_lik[0,4]	-5.37	4.1e-3	0.26	-5.9	-5.54	-5.37	-5.2	-4.88	4000	1.0
log_lik[1,4]	-2.78	8.0e-4	0.05	-2.89	-2.81	-2.78	-2.75	-2.69	4000	1.0
log_lik[2,4]	-3.98	2.4e-3	0.15	-4.28	-4.07	-3.97	-3.88	-3.69	4000	1.0
log_lik[3,4]	-2.68	6.3e-4	0.04	-2.76	-2.7	-2.68	-2.65	-2.6	4000	1.0
log_lik[4,4]	-2.78	8.0e-4	0.05	-2.89	-2.81	-2.78	-2.75	-2.69	4000	1.0
log_lik[5,4]	-3.18	1.4e-3	0.09	-3.37	-3.24	-3.18	-3.13	-3.03	4000	1.0
log_lik[6,4]	-3.18	1.4e-3	0.09	-3.37	-3.24	-3.18	-3.13	-3.03	4000	1.0
log_lik[7,4]	-3.87	2.2e-3	0.14	-4.17	-3.95	-3.86	-3.78	-3.61	4000	1.0
log_lik[8,4]	-2.78	8.0e-4	0.05	-2.89	-2.81	-2.78	-2.75	-2.69	4000	1.0
log_lik[9,4]	-2.88	9.6e-4	0.06	-3.02	-2.92	-2.88	-2.84	-2.77	4000	1.0
log_lik[10,4]	-2.67	6.2e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[11,4]	-4.28	2.7e-3	0.17	-4.64	-4.39	-4.27	-4.16	-3.94	4000	1.0
log_lik[12,4]	-2.82	8.4e-4	0.05	-2.93	-2.85	-2.81	-2.78	-2.71	4000	1.0
log_lik[13,4]	-3.25	1.4e-3	0.09	-3.44	-3.31	-3.25	-3.2	-3.08	4000	1.0
log_lik[14,4]	-2.93	1.0e-3	0.06	-3.06	-2.97	-2.93	-2.89	-2.81	4000	1.0
log_lik[15,4]	-2.78	8.0e-4	0.05	-2.89	-2.81	-2.78	-2.75	-2.69	4000	1.0
log_lik[16,4]	-3.18	1.4e-3	0.09	-3.37	-3.24	-3.18	-3.13	-3.03	4000	1.0
log_lik[17,4]	-3.18	1.4e-3	0.09	-3.37	-3.24	-3.18	-3.13	-3.03	4000	1.0
log_lik[18,4]	-5.22	3.8e-3	0.24	-5.73	-5.37	-5.22	-5.06	-4.76	4000	1.0
log_lik[19,4]	-2.93	1.0e-3	0.06	-3.06	-2.97	-2.93	-2.89	-2.81	4000	1.0
log_lik[20,4]	-2.68	6.3e-4	0.04	-2.76	-2.7	-2.68	-2.65	-2.6	4000	1.0
log_lik[21,4]	-2.67	6.2e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[22,4]	-2.82	8.4e-4	0.05	-2.93	-2.85	-2.81	-2.78	-2.71	4000	1.0
log_lik[23,4]	-2.73	7.2e-4	0.05	-2.83	-2.76	-2.73	-2.7	-2.65	4000	1.0

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log_lik[24,4]  -2.93  1.0e-3   0.06  -3.06  -2.97  -2.93  -2.89  -2.81   4000    1.0
log_lik[25,4]  -2.68  6.3e-4   0.04  -2.76   -2.7  -2.68  -2.65   -2.6   4000    1.0
log_lik[26,4]  -4.61  3.1e-3    0.2  -5.03  -4.74  -4.61  -4.48  -4.23   4000    1.0
log_lik[27,4]   -3.7  2.0e-3   0.13  -3.97  -3.78   -3.7  -3.62  -3.46   4000    1.0
log_lik[28,4]  -3.08  1.2e-3   0.08  -3.24  -3.12  -3.07  -3.03  -2.93   4000    1.0
log_lik[29,4]  -2.67  6.2e-4   0.04  -2.75  -2.69  -2.67  -2.64  -2.59   4000    1.0
log_lik[30,4]  -3.61  1.9e-3   0.12  -3.87  -3.68   -3.6  -3.54  -3.39   4000    1.0
log_lik[31,4]  -2.78  8.0e-4   0.05  -2.89  -2.81  -2.78  -2.75  -2.69   4000    1.0
log_lik[32,4]  -2.88  9.6e-4   0.06  -3.02  -2.92  -2.88  -2.84  -2.77   4000    1.0
log_lik[33,4]  -2.78  8.0e-4   0.05  -2.89  -2.81  -2.78  -2.75  -2.69   4000    1.0
log_lik[34,4]  -2.71  6.9e-4   0.04   -2.8  -2.74  -2.71  -2.68  -2.63   4000    1.0
log_lik[35,4]  -4.28  2.7e-3   0.17  -4.64  -4.39  -4.27  -4.16  -3.94   4000    1.0
log_lik[36,4]  -2.71  6.9e-4   0.04   -2.8  -2.74  -2.71  -2.68  -2.63   4000    1.0
log_lik[37,4]  -2.68  6.3e-4   0.04  -2.76   -2.7  -2.68  -2.65   -2.6   4000    1.0
log_lik[38,4]  -2.78  8.0e-4   0.05  -2.89  -2.81  -2.78  -2.75  -2.69   4000    1.0
log_lik[39,4]  -2.71  6.9e-4   0.04   -2.8  -2.74  -2.71  -2.68  -2.63   4000    1.0
log_lik[40,4]  -2.88  9.6e-4   0.06  -3.02  -2.92  -2.88  -2.84  -2.77   4000    1.0
log_lik[41,4]   -3.7  2.0e-3   0.13  -3.97  -3.78   -3.7  -3.62  -3.46   4000    1.0
log_lik[42,4]  -2.71  6.9e-4   0.04   -2.8  -2.74  -2.71  -2.68  -2.63   4000    1.0
log_lik[43,4]  -2.71  6.9e-4   0.04   -2.8  -2.74  -2.71  -2.68  -2.63   4000    1.0
log_lik[44,4]  -3.25  1.4e-3   0.09  -3.44  -3.31  -3.25   -3.2  -3.08   4000    1.0
log_lik[45,4]  -2.71  6.9e-4   0.04   -2.8  -2.74  -2.71  -2.68  -2.63   4000    1.0
log_lik[46,4]  -3.61  1.9e-3   0.12  -3.87  -3.68   -3.6  -3.54  -3.39   4000    1.0
log_lik[47,4]  -2.88  9.6e-4   0.06  -3.02  -2.92  -2.88  -2.84  -2.77   4000    1.0
log_lik[48,4]  -3.61  1.9e-3   0.12  -3.87  -3.68   -3.6  -3.54  -3.39   4000    1.0
log_lik[49,4]   -3.7  2.0e-3   0.13  -3.97  -3.78   -3.7  -3.62  -3.46   4000    1.0
log_lik[50,4]  -2.67  6.2e-4   0.04  -2.75  -2.69  -2.67  -2.64  -2.59   4000    1.0
log_lik[51,4]  -2.71  6.9e-4   0.04   -2.8  -2.74  -2.71  -2.68  -2.63   4000    1.0
log_lik[52,4]  -2.71  6.9e-4   0.04   -2.8  -2.74  -2.71  -2.68  -2.63   4000    1.0
log_lik[53,4]   -3.7  2.0e-3   0.13  -3.97  -3.78   -3.7  -3.62  -3.46   4000    1.0
log_lik[54,4]  -2.66  6.0e-4   0.04  -2.73  -2.68  -2.66  -2.63  -2.58   4000    1.0
log_lik[55,4]  -2.82  8.4e-4   0.05  -2.93  -2.85  -2.81  -2.78  -2.71   4000    1.0
log_lik[56,4]  -2.78  8.0e-4   0.05  -2.89  -2.81  -2.78  -2.75  -2.69   4000    1.0
log_lik[57,4]  -2.73  7.2e-4   0.05  -2.83  -2.76  -2.73   -2.7  -2.65   4000    1.0
log_lik[58,4]  -3.25  1.4e-3   0.09  -3.44  -3.31  -3.25   -3.2  -3.08   4000    1.0
log_lik[59,4]  -2.93  1.0e-3   0.06  -3.06  -2.97  -2.93  -2.89  -2.81   4000    1.0
log_lik[60,4]  -2.78  8.0e-4   0.05  -2.89  -2.81  -2.78  -2.75  -2.69   4000    1.0
log_lik[61,4]  -4.84  3.4e-3   0.21  -5.29  -4.97  -4.83   -4.7  -4.44   4000    1.0
log_lik[62,4]  -3.38  1.6e-3    0.1  -3.61  -3.44  -3.38  -3.32  -3.19   4000    1.0
log_lik[63,4]  -3.61  1.9e-3   0.12  -3.87  -3.68   -3.6  -3.54  -3.39   4000    1.0
log_lik[64,4]  -2.71  6.9e-4   0.04   -2.8  -2.74  -2.71  -2.68  -2.63   4000    1.0
log_lik[65,4]  -2.82  8.4e-4   0.05  -2.93  -2.85  -2.81  -2.78  -2.71   4000    1.0
log_lik[66,4]  -3.46  1.7e-3   0.11  -3.69  -3.53  -3.46  -3.39  -3.26   4000    1.0
ypred[0]       14.17    0.09   5.63   2.93  10.34  14.11  17.91   25.5   3712    1.0
ypred[1]       14.32    0.09   5.72   2.96  10.46  14.23  18.35  25.13   3657    1.0
ypred[2]       14.22    0.09   5.69   2.71  10.53  14.23  18.08  25.33   4000    1.0
ypred[3]       14.41    0.09   5.78   2.92  10.63  14.34  18.28  25.82   3825    1.0
ypred[4]        14.2    0.09   5.64   3.06  10.31  14.24  18.04  24.89   4000    1.0
mu_new         14.22    0.02   0.94  12.45  13.86  14.21  14.57  16.09   2731    1.0
ypred_new       14.2    0.09    5.8   2.84  10.26  14.19  18.17  25.49   4000    1.0
lp__          -749.3    0.07   2.27 -754.3 -750.6 -749.1 -747.7 -745.4   1146    1.0

Samples were drawn using NUTS at Sun Dec  9 13:48:51 2018.
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).

##########################################################################
#### Attachment 4: Fit of hierarchical model with inverse gamma prior ####
##########################################################################

Inference for Stan model: anon_model_48a5c6bedf159373816b9432a8388eb4.
4 chains, each with iter=2000; warmup=1000; thin=1;
post-warmup draws per chain=1000, total post-warmup draws=4000.
```

	mean	se_mean	sd	2.5%	25%	50%	75%	97.5%	n_eff	Rhat
mu0	14.17	0.01	0.43	13.33	13.91	14.18	14.45	15.0	1637	1.0
sigma0	0.55	0.02	0.57	0.02	0.19	0.4	0.73	2.04	913	1.0
mu_tilde[0]	-0.2	0.02	0.88	-1.96	-0.76	-0.21	0.37	1.56	3191	1.0
mu_tilde[1]	0.12	0.02	0.88	-1.68	-0.43	0.1	0.7	1.83	2959	1.0
mu_tilde[2]	-0.2	0.01	0.86	-1.94	-0.75	-0.22	0.35	1.49	3433	1.0
mu_tilde[3]	0.37	0.02	0.85	-1.42	-0.16	0.38	0.93	2.05	3213	1.0
mu_tilde[4]	3.1e-3	0.01	0.84	-1.68	-0.54	-1.8e-3	0.53	1.75	3325	1.0
sigmaSq	31.97	0.04	2.56	27.37	30.2	31.81	33.63	37.32	4000	1.0
mu[0]	14.06	7.7e-3	0.48	13.02	13.77	14.09	14.39	14.96	4000	1.0
mu[1]	14.25	7.5e-3	0.47	13.32	13.96	14.24	14.55	15.22	4000	1.0
mu[2]	14.05	7.7e-3	0.49	13.0	13.75	14.08	14.36	14.94	4000	1.0
mu[3]	14.41	7.8e-3	0.49	13.54	14.06	14.38	14.71	15.49	4000	1.0
mu[4]	14.18	7.4e-3	0.47	13.23	13.9	14.19	14.49	15.1	4000	1.0
sigma	5.65	3.6e-3	0.23	5.23	5.5	5.64	5.8	6.11	4000	1.0
log_lik[0,0]	-3.68	2.0e-3	0.13	-3.93	-3.76	-3.68	-3.59	-3.42	4000	1.0
log_lik[1,0]	-2.67	6.6e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[2,0]	-2.71	7.3e-4	0.05	-2.81	-2.74	-2.71	-2.68	-2.63	4000	1.0
log_lik[3,0]	-2.67	6.6e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[4,0]	-3.04	1.2e-3	0.08	-3.21	-3.08	-3.03	-2.99	-2.91	4000	1.0
log_lik[5,0]	-2.79	8.5e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.69	4000	1.0
log_lik[6,0]	-2.79	8.5e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.69	4000	1.0
log_lik[7,0]	-2.79	8.5e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.69	4000	1.0
log_lik[8,0]	-3.95	2.4e-3	0.15	-4.24	-4.04	-3.95	-3.85	-3.64	4000	1.0
log_lik[9,0]	-2.79	8.5e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.69	4000	1.0
log_lik[10,0]	-2.79	8.5e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.69	4000	1.0
log_lik[11,0]	-3.06	1.2e-3	0.08	-3.21	-3.11	-3.06	-3.01	-2.9	4000	1.0
log_lik[12,0]	-3.68	2.0e-3	0.13	-3.93	-3.76	-3.68	-3.59	-3.42	4000	1.0
log_lik[13,0]	-2.79	8.5e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.69	4000	1.0
log_lik[14,0]	-3.95	2.4e-3	0.15	-4.24	-4.04	-3.95	-3.85	-3.64	4000	1.0
log_lik[15,0]	-3.68	2.0e-3	0.13	-3.93	-3.76	-3.68	-3.59	-3.42	4000	1.0
log_lik[16,0]	-2.8	8.6e-4	0.05	-2.91	-2.84	-2.8	-2.76	-2.7	4000	1.0
log_lik[17,0]	-3.06	1.2e-3	0.08	-3.21	-3.11	-3.06	-3.01	-2.9	4000	1.0
log_lik[18,0]	-2.71	7.3e-4	0.05	-2.81	-2.74	-2.71	-2.68	-2.63	4000	1.0
log_lik[19,0]	-3.41	1.7e-3	0.11	-3.65	-3.47	-3.4	-3.34	-3.22	4000	1.0
log_lik[20,0]	-2.79	8.5e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.69	4000	1.0
log_lik[21,0]	-2.67	6.6e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[22,0]	-4.21	2.8e-3	0.18	-4.6	-4.32	-4.19	-4.09	-3.89	4000	1.0
log_lik[23,0]	-2.91	1.0e-3	0.06	-3.04	-2.96	-2.91	-2.87	-2.79	4000	1.0
log_lik[24,0]	-3.06	1.2e-3	0.08	-3.21	-3.11	-3.06	-3.01	-2.9	4000	1.0
log_lik[25,0]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.17	-3.05	4000	1.0
log_lik[26,0]	-3.65	2.0e-3	0.13	-3.93	-3.72	-3.63	-3.56	-3.42	4000	1.0
log_lik[27,0]	-2.72	7.4e-4	0.05	-2.81	-2.75	-2.72	-2.69	-2.63	4000	1.0
log_lik[28,0]	-3.04	1.2e-3	0.08	-3.21	-3.08	-3.03	-2.99	-2.91	4000	1.0
log_lik[29,0]	-3.06	1.2e-3	0.08	-3.21	-3.11	-3.06	-3.01	-2.9	4000	1.0
log_lik[30,0]	-2.67	6.6e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[31,0]	-2.72	7.4e-4	0.05	-2.81	-2.75	-2.72	-2.69	-2.63	4000	1.0
log_lik[32,0]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.17	-3.05	4000	1.0
log_lik[33,0]	-2.79	8.5e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.69	4000	1.0
log_lik[34,0]	-2.67	6.6e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[35,0]	-4.54	3.2e-3	0.2	-4.98	-4.66	-4.52	-4.39	-4.18	4000	1.0
log_lik[36,0]	-3.04	1.2e-3	0.08	-3.21	-3.08	-3.03	-2.99	-2.91	4000	1.0
log_lik[37,0]	-4.21	2.8e-3	0.18	-4.6	-4.32	-4.19	-4.09	-3.89	4000	1.0
log_lik[38,0]	-2.71	7.3e-4	0.05	-2.81	-2.74	-2.71	-2.68	-2.63	4000	1.0
log_lik[39,0]	-3.95	2.4e-3	0.15	-4.24	-4.04	-3.95	-3.85	-3.64	4000	1.0
log_lik[40,0]	-2.79	8.5e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.69	4000	1.0
log_lik[41,0]	-3.21	1.5e-3	0.09	-3.41	-3.26	-3.2	-3.15	-3.05	4000	1.0
log_lik[42,0]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.17	-3.05	4000	1.0
log_lik[43,0]	-3.65	2.0e-3	0.13	-3.93	-3.72	-3.63	-3.56	-3.42	4000	1.0
log_lik[44,0]	-2.67	6.6e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[45,0]	-3.68	2.0e-3	0.13	-3.93	-3.76	-3.68	-3.59	-3.42	4000	1.0
log_lik[46,0]	-3.68	2.0e-3	0.13	-3.93	-3.76	-3.68	-3.59	-3.42	4000	1.0
log_lik[47,0]	-3.06	1.2e-3	0.08	-3.21	-3.11	-3.06	-3.01	-2.9	4000	1.0

log_lik[48,0]	-3.23	1.4e-3	0.09	-3.41	-3.29	-3.23	-3.17	-3.05	4000	1.0
log_lik[49,0]	-2.79	8.5e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.69	4000	1.0
log_lik[50,0]	-3.41	1.7e-3	0.11	-3.65	-3.47	-3.4	-3.34	-3.22	4000	1.0
log_lik[51,0]	-3.04	1.2e-3	0.08	-3.21	-3.08	-3.03	-2.99	-2.91	4000	1.0
log_lik[52,0]	-3.65	2.0e-3	0.13	-3.93	-3.72	-3.63	-3.56	-3.42	4000	1.0
log_lik[53,0]	-4.25	2.7e-3	0.17	-4.59	-4.36	-4.25	-4.13	-3.9	4000	1.0
log_lik[54,0]	-3.06	1.2e-3	0.08	-3.21	-3.11	-3.06	-3.01	-2.9	4000	1.0
log_lik[55,0]	-2.71	7.3e-4	0.05	-2.81	-2.74	-2.71	-2.68	-2.63	4000	1.0
log_lik[56,0]	-2.9	1.0e-3	0.06	-3.04	-2.93	-2.89	-2.86	-2.79	4000	1.0
log_lik[57,0]	-2.72	7.4e-4	0.05	-2.81	-2.75	-2.72	-2.69	-2.63	4000	1.0
log_lik[58,0]	-2.67	6.6e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[59,0]	-2.91	1.0e-3	0.06	-3.04	-2.96	-2.91	-2.87	-2.79	4000	1.0
log_lik[60,0]	-3.68	2.0e-3	0.13	-3.93	-3.76	-3.68	-3.59	-3.42	4000	1.0
log_lik[61,0]	-2.91	1.0e-3	0.06	-3.04	-2.96	-2.91	-2.87	-2.79	4000	1.0
log_lik[62,0]	-3.68	2.0e-3	0.13	-3.93	-3.76	-3.68	-3.59	-3.42	4000	1.0
log_lik[63,0]	-3.44	1.7e-3	0.11	-3.65	-3.51	-3.44	-3.37	-3.22	4000	1.0
log_lik[64,0]	-2.71	7.3e-4	0.05	-2.81	-2.74	-2.71	-2.68	-2.63	4000	1.0
log_lik[65,0]	-3.21	1.5e-3	0.09	-3.41	-3.26	-3.2	-3.15	-3.05	4000	1.0
log_lik[66,0]	-3.65	2.0e-3	0.13	-3.93	-3.72	-3.63	-3.56	-3.42	4000	1.0
log_lik[0,1]	-2.77	7.9e-4	0.05	-2.88	-2.8	-2.77	-2.74	-2.68	4000	1.0
log_lik[1,1]	-2.66	6.4e-4	0.04	-2.74	-2.69	-2.66	-2.63	-2.58	4000	1.0
log_lik[2,1]	-3.48	1.8e-3	0.11	-3.72	-3.55	-3.47	-3.41	-3.27	4000	1.0
log_lik[3,1]	-2.68	6.8e-4	0.04	-2.77	-2.71	-2.68	-2.65	-2.6	4000	1.0
log_lik[4,1]	-3.17	1.3e-3	0.09	-3.35	-3.23	-3.17	-3.12	-3.01	4000	1.0
log_lik[5,1]	-3.17	1.3e-3	0.09	-3.35	-3.23	-3.17	-3.12	-3.01	4000	1.0
log_lik[6,1]	-2.7	7.0e-4	0.04	-2.79	-2.73	-2.7	-2.67	-2.62	4000	1.0
log_lik[7,1]	-5.21	4.0e-3	0.25	-5.73	-5.38	-5.2	-5.04	-4.73	4000	1.0
log_lik[8,1]	-2.77	7.9e-4	0.05	-2.88	-2.8	-2.77	-2.74	-2.68	4000	1.0
log_lik[9,1]	-2.73	7.7e-4	0.05	-2.83	-2.76	-2.73	-2.7	-2.64	4000	1.0
log_lik[10,1]	-2.65	6.4e-4	0.04	-2.73	-2.68	-2.65	-2.63	-2.58	4000	1.0
log_lik[11,1]	-2.77	7.9e-4	0.05	-2.88	-2.8	-2.77	-2.74	-2.68	4000	1.0
log_lik[12,1]	-3.37	1.6e-3	0.1	-3.59	-3.43	-3.37	-3.3	-3.17	4000	1.0
log_lik[13,1]	-3.48	1.8e-3	0.11	-3.72	-3.55	-3.47	-3.41	-3.27	4000	1.0
log_lik[14,1]	-2.82	8.9e-4	0.06	-2.94	-2.85	-2.82	-2.78	-2.72	4000	1.0
log_lik[15,1]	-3.73	2.1e-3	0.13	-4.01	-3.8	-3.72	-3.64	-3.49	4000	1.0
log_lik[16,1]	-2.68	6.8e-4	0.04	-2.77	-2.71	-2.68	-2.65	-2.6	4000	1.0
log_lik[17,1]	-3.27	1.5e-3	0.09	-3.48	-3.32	-3.26	-3.21	-3.1	4000	1.0
log_lik[18,1]	-2.73	7.7e-4	0.05	-2.83	-2.76	-2.73	-2.7	-2.64	4000	1.0
log_lik[19,1]	-3.01	1.1e-3	0.07	-3.16	-3.05	-3.01	-2.96	-2.87	4000	1.0
log_lik[20,1]	-3.17	1.3e-3	0.09	-3.35	-3.23	-3.17	-3.12	-3.01	4000	1.0
log_lik[21,1]	-2.87	9.4e-4	0.06	-3.0	-2.91	-2.87	-2.84	-2.76	4000	1.0
log_lik[22,1]	-4.15	2.6e-3	0.17	-4.49	-4.25	-4.14	-4.04	-3.83	4000	1.0
log_lik[23,1]	-3.09	1.3e-3	0.08	-3.26	-3.13	-3.08	-3.04	-2.94	4000	1.0
log_lik[24,1]	-2.68	6.8e-4	0.04	-2.77	-2.71	-2.68	-2.65	-2.6	4000	1.0
log_lik[25,1]	-2.87	9.4e-4	0.06	-3.0	-2.91	-2.87	-2.84	-2.76	4000	1.0
log_lik[26,1]	-3.37	1.6e-3	0.1	-3.59	-3.43	-3.37	-3.3	-3.17	4000	1.0
log_lik[27,1]	-2.66	6.4e-4	0.04	-2.74	-2.69	-2.66	-2.63	-2.58	4000	1.0
log_lik[28,1]	-2.65	6.4e-4	0.04	-2.73	-2.68	-2.65	-2.63	-2.58	4000	1.0
log_lik[29,1]	-3.09	1.3e-3	0.08	-3.26	-3.13	-3.08	-3.04	-2.94	4000	1.0
log_lik[30,1]	-3.73	2.1e-3	0.13	-4.01	-3.8	-3.72	-3.64	-3.49	4000	1.0
log_lik[31,1]	-2.77	7.9e-4	0.05	-2.88	-2.8	-2.77	-2.74	-2.68	4000	1.0
log_lik[32,1]	-4.65	3.2e-3	0.2	-5.07	-4.77	-4.64	-4.51	-4.27	4000	1.0
log_lik[33,1]	-2.66	6.4e-4	0.04	-2.74	-2.69	-2.66	-2.63	-2.58	4000	1.0
log_lik[34,1]	-2.7	7.0e-4	0.04	-2.79	-2.73	-2.7	-2.67	-2.62	4000	1.0
log_lik[35,1]	-3.17	1.3e-3	0.09	-3.35	-3.23	-3.17	-3.12	-3.01	4000	1.0
log_lik[36,1]	-2.77	7.9e-4	0.05	-2.88	-2.8	-2.77	-2.74	-2.68	4000	1.0
log_lik[37,1]	-4.47	3.1e-3	0.19	-4.87	-4.59	-4.47	-4.34	-4.1	4000	1.0
log_lik[38,1]	-3.73	2.1e-3	0.13	-4.01	-3.8	-3.72	-3.64	-3.49	4000	1.0
log_lik[39,1]	-2.77	7.9e-4	0.05	-2.88	-2.8	-2.77	-2.74	-2.68	4000	1.0
log_lik[40,1]	-2.7	7.0e-4	0.04	-2.79	-2.73	-2.7	-2.67	-2.62	4000	1.0
log_lik[41,1]	-3.48	1.8e-3	0.11	-3.72	-3.55	-3.47	-3.41	-3.27	4000	1.0
log_lik[42,1]	-3.73	2.1e-3	0.13	-4.01	-3.8	-3.72	-3.64	-3.49	4000	1.0
log_lik[43,1]	-3.09	1.3e-3	0.08	-3.26	-3.13	-3.08	-3.04	-2.94	4000	1.0
log_lik[44,1]	-2.65	6.4e-4	0.04	-2.73	-2.68	-2.65	-2.63	-2.58	4000	1.0

log_lik[45,1]	-3.73	2.1e-3	0.13	-4.01	-3.8	-3.72	-3.64	-3.49	4000	1.0
log_lik[46,1]	-2.68	6.8e-4	0.04	-2.77	-2.71	-2.68	-2.65	-2.6	4000	1.0
log_lik[47,1]	-3.27	1.5e-3	0.09	-3.48	-3.32	-3.26	-3.21	-3.1	4000	1.0
log_lik[48,1]	-2.94	1.1e-3	0.07	-3.08	-2.98	-2.93	-2.89	-2.82	4000	1.0
log_lik[49,1]	-2.87	9.4e-4	0.06	-3.0	-2.91	-2.87	-2.84	-2.76	4000	1.0
log_lik[50,1]	-4.47	3.1e-3	0.19	-4.87	-4.59	-4.47	-4.34	-4.1	4000	1.0
log_lik[51,1]	-2.77	7.9e-4	0.05	-2.88	-2.8	-2.77	-2.74	-2.68	4000	1.0
log_lik[52,1]	-3.6	1.9e-3	0.12	-3.85	-3.67	-3.6	-3.52	-3.36	4000	1.0
log_lik[53,1]	-2.94	1.1e-3	0.07	-3.08	-2.98	-2.93	-2.89	-2.82	4000	1.0
log_lik[54,1]	-2.66	6.4e-4	0.04	-2.74	-2.69	-2.66	-2.63	-2.58	4000	1.0
log_lik[55,1]	-3.73	2.1e-3	0.13	-4.01	-3.8	-3.72	-3.64	-3.49	4000	1.0
log_lik[56,1]	-2.77	7.9e-4	0.05	-2.88	-2.8	-2.77	-2.74	-2.68	4000	1.0
log_lik[57,1]	-2.82	8.9e-4	0.06	-2.94	-2.85	-2.82	-2.78	-2.72	4000	1.0
log_lik[58,1]	-3.6	1.9e-3	0.12	-3.85	-3.67	-3.6	-3.52	-3.36	4000	1.0
log_lik[59,1]	-2.87	9.4e-4	0.06	-3.0	-2.91	-2.87	-2.84	-2.76	4000	1.0
log_lik[60,1]	-2.77	7.9e-4	0.05	-2.88	-2.8	-2.77	-2.74	-2.68	4000	1.0
log_lik[61,1]	-2.68	6.8e-4	0.04	-2.77	-2.71	-2.68	-2.65	-2.6	4000	1.0
log_lik[62,1]	-4.31	2.8e-3	0.18	-4.68	-4.42	-4.3	-4.19	-3.98	4000	1.0
log_lik[63,1]	-2.94	1.1e-3	0.07	-3.08	-2.98	-2.93	-2.89	-2.82	4000	1.0
log_lik[64,1]	-2.87	9.4e-4	0.06	-3.0	-2.91	-2.87	-2.84	-2.76	4000	1.0
log_lik[65,1]	-3.17	1.3e-3	0.09	-3.35	-3.23	-3.17	-3.12	-3.01	4000	1.0
log_lik[66,1]	-2.77	7.9e-4	0.05	-2.88	-2.8	-2.77	-2.74	-2.68	4000	1.0
log_lik[0,2]	-2.71	7.5e-4	0.05	-2.81	-2.74	-2.71	-2.68	-2.63	4000	1.0
log_lik[1,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[2,2]	-4.24	2.8e-3	0.17	-4.58	-4.36	-4.24	-4.13	-3.9	4000	1.0
log_lik[3,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[4,2]	-3.21	1.5e-3	0.09	-3.42	-3.26	-3.2	-3.15	-3.06	4000	1.0
log_lik[5,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[6,2]	-2.67	6.7e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[7,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[8,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[9,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[10,2]	-3.94	2.4e-3	0.15	-4.24	-4.04	-3.94	-3.84	-3.65	4000	1.0
log_lik[11,2]	-2.71	7.5e-4	0.05	-2.81	-2.74	-2.71	-2.68	-2.63	4000	1.0
log_lik[12,2]	-2.71	7.5e-4	0.05	-2.81	-2.74	-2.71	-2.68	-2.63	4000	1.0
log_lik[13,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[14,2]	-2.71	7.5e-4	0.05	-2.81	-2.74	-2.71	-2.68	-2.63	4000	1.0
log_lik[15,2]	-3.67	2.0e-3	0.13	-3.92	-3.75	-3.67	-3.59	-3.41	4000	1.0
log_lik[16,2]	-2.8	8.5e-4	0.05	-2.91	-2.83	-2.8	-2.76	-2.69	4000	1.0
log_lik[17,2]	-3.05	1.2e-3	0.08	-3.2	-3.1	-3.06	-3.01	-2.9	4000	1.0
log_lik[18,2]	-2.91	1.0e-3	0.06	-3.04	-2.95	-2.91	-2.87	-2.78	4000	1.0
log_lik[19,2]	-2.67	6.7e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[20,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[21,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[22,2]	-3.65	2.1e-3	0.13	-3.95	-3.72	-3.64	-3.56	-3.42	4000	1.0
log_lik[23,2]	-3.23	1.4e-3	0.09	-3.4	-3.29	-3.23	-3.17	-3.04	4000	1.0
log_lik[24,2]	-3.23	1.4e-3	0.09	-3.4	-3.29	-3.23	-3.17	-3.04	4000	1.0
log_lik[25,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[26,2]	-3.65	2.1e-3	0.13	-3.95	-3.72	-3.64	-3.56	-3.42	4000	1.0
log_lik[27,2]	-2.67	6.7e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[28,2]	-3.92	2.4e-3	0.15	-4.26	-4.0	-3.9	-3.81	-3.65	4000	1.0
log_lik[29,2]	-3.04	1.2e-3	0.08	-3.22	-3.08	-3.03	-2.99	-2.91	4000	1.0
log_lik[30,2]	-3.67	2.0e-3	0.13	-3.92	-3.75	-3.67	-3.59	-3.41	4000	1.0
log_lik[31,2]	-3.23	1.4e-3	0.09	-3.4	-3.29	-3.23	-3.17	-3.04	4000	1.0
log_lik[32,2]	-3.23	1.4e-3	0.09	-3.4	-3.29	-3.23	-3.17	-3.04	4000	1.0
log_lik[33,2]	-3.67	2.0e-3	0.13	-3.92	-3.75	-3.67	-3.59	-3.41	4000	1.0
log_lik[34,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[35,2]	-2.67	6.7e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[36,2]	-2.67	6.7e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[37,2]	-4.9	3.7e-3	0.23	-5.42	-5.04	-4.88	-4.74	-4.49	4000	1.0
log_lik[38,2]	-2.67	6.6e-4	0.04	-2.75	-2.7	-2.67	-2.64	-2.59	4000	1.0
log_lik[39,2]	-3.23	1.4e-3	0.09	-3.4	-3.29	-3.23	-3.17	-3.04	4000	1.0
log_lik[40,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[41,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0

log_lik[42,2]	-2.67	6.7e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[43,2]	-2.67	6.7e-4	0.04	-2.75	-2.69	-2.67	-2.64	-2.59	4000	1.0
log_lik[44,2]	-3.67	2.0e-3	0.13	-3.92	-3.75	-3.67	-3.59	-3.41	4000	1.0
log_lik[45,2]	-3.67	2.0e-3	0.13	-3.92	-3.75	-3.67	-3.59	-3.41	4000	1.0
log_lik[46,2]	-2.91	1.0e-3	0.06	-3.04	-2.95	-2.91	-2.87	-2.78	4000	1.0
log_lik[47,2]	-3.23	1.4e-3	0.09	-3.4	-3.29	-3.23	-3.17	-3.04	4000	1.0
log_lik[48,2]	-2.8	8.5e-4	0.05	-2.91	-2.83	-2.8	-2.76	-2.69	4000	1.0
log_lik[49,2]	-3.92	2.4e-3	0.15	-4.26	-4.0	-3.9	-3.81	-3.65	4000	1.0
log_lik[50,2]	-3.21	1.5e-3	0.09	-3.42	-3.26	-3.2	-3.15	-3.06	4000	1.0
log_lik[51,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[52,2]	-3.67	2.0e-3	0.13	-3.92	-3.75	-3.67	-3.59	-3.41	4000	1.0
log_lik[53,2]	-2.91	1.0e-3	0.06	-3.04	-2.95	-2.91	-2.87	-2.78	4000	1.0
log_lik[54,2]	-3.23	1.4e-3	0.09	-3.4	-3.29	-3.23	-3.17	-3.04	4000	1.0
log_lik[55,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[56,2]	-2.71	7.5e-4	0.05	-2.81	-2.74	-2.71	-2.68	-2.63	4000	1.0
log_lik[57,2]	-4.21	2.8e-3	0.18	-4.61	-4.32	-4.2	-4.09	-3.91	4000	1.0
log_lik[58,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[59,2]	-2.79	8.7e-4	0.05	-2.91	-2.82	-2.79	-2.75	-2.7	4000	1.0
log_lik[60,2]	-2.72	7.3e-4	0.05	-2.81	-2.75	-2.72	-2.69	-2.63	4000	1.0
log_lik[61,2]	-3.23	1.4e-3	0.09	-3.4	-3.29	-3.23	-3.17	-3.04	4000	1.0
log_lik[62,2]	-2.67	6.6e-4	0.04	-2.75	-2.7	-2.67	-2.64	-2.59	4000	1.0
log_lik[63,2]	-3.23	1.4e-3	0.09	-3.4	-3.29	-3.23	-3.17	-3.04	4000	1.0
log_lik[64,2]	-2.65	6.4e-4	0.04	-2.73	-2.68	-2.65	-2.63	-2.58	4000	1.0
log_lik[65,2]	-2.67	6.6e-4	0.04	-2.75	-2.7	-2.67	-2.64	-2.59	4000	1.0
log_lik[66,2]	-3.94	2.4e-3	0.15	-4.24	-4.04	-3.94	-3.84	-3.65	4000	1.0
log_lik[0,3]	-3.77	2.3e-3	0.14	-4.09	-3.85	-3.75	-3.67	-3.53	4000	1.0
log_lik[1,3]	-2.68	7.0e-4	0.04	-2.78	-2.71	-2.68	-2.66	-2.6	4000	1.0
log_lik[2,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[3,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[4,3]	-2.66	6.4e-4	0.04	-2.74	-2.69	-2.66	-2.63	-2.58	4000	1.0
log_lik[5,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[6,3]	-4.1	2.6e-3	0.17	-4.43	-4.21	-4.1	-3.99	-3.77	4000	1.0
log_lik[7,3]	-4.77	3.5e-3	0.22	-5.21	-4.92	-4.77	-4.62	-4.34	4000	1.0
log_lik[8,3]	-2.96	1.1e-3	0.07	-3.12	-3.0	-2.95	-2.91	-2.84	4000	1.0
log_lik[9,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[10,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[11,3]	-2.69	6.9e-4	0.04	-2.78	-2.72	-2.69	-2.66	-2.61	4000	1.0
log_lik[12,3]	-4.05	2.6e-3	0.17	-4.42	-4.14	-4.03	-3.93	-3.77	4000	1.0
log_lik[13,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[14,3]	-3.77	2.3e-3	0.14	-4.09	-3.85	-3.75	-3.67	-3.53	4000	1.0
log_lik[15,3]	-2.66	6.4e-4	0.04	-2.74	-2.69	-2.66	-2.63	-2.58	4000	1.0
log_lik[16,3]	-3.11	1.4e-3	0.09	-3.32	-3.16	-3.1	-3.05	-2.97	4000	1.0
log_lik[17,3]	-4.36	3.0e-3	0.19	-4.79	-4.47	-4.34	-4.23	-4.03	4000	1.0
log_lik[18,3]	-2.96	1.1e-3	0.07	-3.12	-3.0	-2.95	-2.91	-2.84	4000	1.0
log_lik[19,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[20,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[21,3]	-2.66	6.4e-4	0.04	-2.74	-2.69	-2.66	-2.63	-2.58	4000	1.0
log_lik[22,3]	-3.56	1.9e-3	0.12	-3.79	-3.64	-3.56	-3.48	-3.32	4000	1.0
log_lik[23,3]	-2.69	6.9e-4	0.04	-2.78	-2.72	-2.69	-2.66	-2.61	4000	1.0
log_lik[24,3]	-3.34	1.6e-3	0.1	-3.53	-3.41	-3.34	-3.27	-3.13	4000	1.0
log_lik[25,3]	-2.96	1.1e-3	0.07	-3.12	-3.0	-2.95	-2.91	-2.84	4000	1.0
log_lik[26,3]	-3.56	1.9e-3	0.12	-3.79	-3.64	-3.56	-3.48	-3.32	4000	1.0
log_lik[27,3]	-2.99	1.1e-3	0.07	-3.12	-3.03	-2.99	-2.94	-2.84	4000	1.0
log_lik[28,3]	-3.34	1.6e-3	0.1	-3.53	-3.41	-3.34	-3.27	-3.13	4000	1.0
log_lik[29,3]	-2.66	6.4e-4	0.04	-2.74	-2.69	-2.66	-2.63	-2.58	4000	1.0
log_lik[30,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[31,3]	-2.69	6.9e-4	0.04	-2.78	-2.72	-2.69	-2.66	-2.61	4000	1.0
log_lik[32,3]	-3.3	1.6e-3	0.1	-3.54	-3.36	-3.29	-3.23	-3.13	4000	1.0
log_lik[33,3]	-2.96	1.1e-3	0.07	-3.12	-3.0	-2.95	-2.91	-2.84	4000	1.0
log_lik[34,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[35,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[36,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[37,3]	-5.15	4.0e-3	0.25	-5.66	-5.32	-5.14	-4.98	-4.67	4000	1.0
log_lik[38,3]	-3.77	2.3e-3	0.14	-4.09	-3.85	-3.75	-3.67	-3.53	4000	1.0

log_lik[39,3]	-2.84	9.6e-4	0.06	-2.97	-2.87	-2.83	-2.79	-2.73	4000	1.0
log_lik[40,3]	-3.11	1.4e-3	0.09	-3.32	-3.16	-3.1	-3.05	-2.97	4000	1.0
log_lik[41,3]	-2.96	1.1e-3	0.07	-3.12	-3.0	-2.95	-2.91	-2.84	4000	1.0
log_lik[42,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[43,3]	-4.77	3.5e-3	0.22	-5.21	-4.92	-4.77	-4.62	-4.34	4000	1.0
log_lik[44,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[45,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[46,3]	-2.74	8.1e-4	0.05	-2.85	-2.78	-2.74	-2.71	-2.65	4000	1.0
log_lik[47,3]	-2.84	9.6e-4	0.06	-2.97	-2.87	-2.83	-2.79	-2.73	4000	1.0
log_lik[48,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[49,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[50,3]	-3.3	1.6e-3	0.1	-3.54	-3.36	-3.29	-3.23	-3.13	4000	1.0
log_lik[51,3]	-2.69	6.9e-4	0.04	-2.78	-2.72	-2.69	-2.66	-2.61	4000	1.0
log_lik[52,3]	-3.3	1.6e-3	0.1	-3.54	-3.36	-3.29	-3.23	-3.13	4000	1.0
log_lik[53,3]	-3.77	2.3e-3	0.14	-4.09	-3.85	-3.75	-3.67	-3.53	4000	1.0
log_lik[54,3]	-2.84	9.6e-4	0.06	-2.97	-2.87	-2.83	-2.79	-2.73	4000	1.0
log_lik[55,3]	-4.7	3.5e-3	0.22	-5.19	-4.83	-4.68	-4.55	-4.32	4000	1.0
log_lik[56,3]	-3.3	1.6e-3	0.1	-3.54	-3.36	-3.29	-3.23	-3.13	4000	1.0
log_lik[57,3]	-3.34	1.6e-3	0.1	-3.53	-3.41	-3.34	-3.27	-3.13	4000	1.0
log_lik[58,3]	-4.1	2.6e-3	0.17	-4.43	-4.21	-4.1	-3.99	-3.77	4000	1.0
log_lik[59,3]	-3.56	1.9e-3	0.12	-3.79	-3.64	-3.56	-3.48	-3.32	4000	1.0
log_lik[60,3]	-3.56	1.9e-3	0.12	-3.79	-3.64	-3.56	-3.48	-3.32	4000	1.0
log_lik[61,3]	-2.84	9.6e-4	0.06	-2.97	-2.87	-2.83	-2.79	-2.73	4000	1.0
log_lik[62,3]	-2.76	8.0e-4	0.05	-2.86	-2.79	-2.76	-2.73	-2.66	4000	1.0
log_lik[63,3]	-2.66	6.4e-4	0.04	-2.74	-2.69	-2.66	-2.63	-2.58	4000	1.0
log_lik[64,3]	-3.56	1.9e-3	0.12	-3.79	-3.64	-3.56	-3.48	-3.32	4000	1.0
log_lik[65,3]	-3.77	2.3e-3	0.14	-4.09	-3.85	-3.75	-3.67	-3.53	4000	1.0
log_lik[66,3]	-3.56	1.9e-3	0.12	-3.79	-3.64	-3.56	-3.48	-3.32	4000	1.0
log_lik[0,4]	-5.39	4.1e-3	0.26	-5.92	-5.56	-5.38	-5.22	-4.89	4000	1.0
log_lik[1,4]	-2.78	8.1e-4	0.05	-2.89	-2.81	-2.78	-2.74	-2.68	4000	1.0
log_lik[2,4]	-3.98	2.4e-3	0.15	-4.28	-4.07	-3.97	-3.88	-3.7	4000	1.0
log_lik[3,4]	-2.68	6.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	4000	1.0
log_lik[4,4]	-2.78	8.1e-4	0.05	-2.89	-2.81	-2.78	-2.74	-2.68	4000	1.0
log_lik[5,4]	-3.19	1.4e-3	0.09	-3.37	-3.24	-3.18	-3.13	-3.03	4000	1.0
log_lik[6,4]	-3.19	1.4e-3	0.09	-3.37	-3.24	-3.18	-3.13	-3.03	4000	1.0
log_lik[7,4]	-3.88	2.3e-3	0.14	-4.18	-3.97	-3.87	-3.78	-3.61	4000	1.0
log_lik[8,4]	-2.78	8.1e-4	0.05	-2.89	-2.81	-2.78	-2.74	-2.68	4000	1.0
log_lik[9,4]	-2.88	9.5e-4	0.06	-3.01	-2.92	-2.88	-2.84	-2.77	4000	1.0
log_lik[10,4]	-2.66	6.5e-4	0.04	-2.75	-2.69	-2.66	-2.64	-2.59	4000	1.0
log_lik[11,4]	-4.29	2.7e-3	0.17	-4.64	-4.39	-4.28	-4.17	-3.96	4000	1.0
log_lik[12,4]	-2.81	8.6e-4	0.05	-2.92	-2.85	-2.81	-2.77	-2.71	4000	1.0
log_lik[13,4]	-3.26	1.4e-3	0.09	-3.44	-3.31	-3.25	-3.2	-3.08	4000	1.0
log_lik[14,4]	-2.93	1.0e-3	0.06	-3.06	-2.97	-2.93	-2.89	-2.81	4000	1.0
log_lik[15,4]	-2.78	8.1e-4	0.05	-2.89	-2.81	-2.78	-2.74	-2.68	4000	1.0
log_lik[16,4]	-3.19	1.4e-3	0.09	-3.37	-3.24	-3.18	-3.13	-3.03	4000	1.0
log_lik[17,4]	-3.19	1.4e-3	0.09	-3.37	-3.24	-3.18	-3.13	-3.03	4000	1.0
log_lik[18,4]	-5.24	4.0e-3	0.25	-5.76	-5.4	-5.23	-5.06	-4.77	4000	1.0
log_lik[19,4]	-2.93	1.0e-3	0.06	-3.06	-2.97	-2.93	-2.89	-2.81	4000	1.0
log_lik[20,4]	-2.68	6.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	4000	1.0
log_lik[21,4]	-2.66	6.5e-4	0.04	-2.75	-2.69	-2.66	-2.64	-2.59	4000	1.0
log_lik[22,4]	-2.81	8.6e-4	0.05	-2.92	-2.85	-2.81	-2.77	-2.71	4000	1.0
log_lik[23,4]	-2.73	7.5e-4	0.05	-2.83	-2.76	-2.73	-2.7	-2.64	4000	1.0
log_lik[24,4]	-2.93	1.0e-3	0.06	-3.06	-2.97	-2.93	-2.89	-2.81	4000	1.0
log_lik[25,4]	-2.68	6.7e-4	0.04	-2.76	-2.7	-2.67	-2.65	-2.6	4000	1.0
log_lik[26,4]	-4.62	3.2e-3	0.2	-5.04	-4.75	-4.61	-4.49	-4.24	4000	1.0
log_lik[27,4]	-3.71	2.0e-3	0.13	-3.97	-3.79	-3.7	-3.62	-3.47	4000	1.0
log_lik[28,4]	-3.08	1.2e-3	0.08	-3.24	-3.12	-3.07	-3.03	-2.93	4000	1.0
log_lik[29,4]	-2.66	6.5e-4	0.04	-2.75	-2.69	-2.66	-2.64	-2.59	4000	1.0
log_lik[30,4]	-3.61	1.9e-3	0.12	-3.87	-3.69	-3.61	-3.53	-3.39	4000	1.0
log_lik[31,4]	-2.78	8.1e-4	0.05	-2.89	-2.81	-2.78	-2.74	-2.68	4000	1.0
log_lik[32,4]	-2.88	9.5e-4	0.06	-3.01	-2.92	-2.88	-2.84	-2.77	4000	1.0
log_lik[33,4]	-2.78	8.1e-4	0.05	-2.89	-2.81	-2.78	-2.74	-2.68	4000	1.0
log_lik[34,4]	-2.71	7.1e-4	0.04	-2.8	-2.73	-2.7	-2.67	-2.62	4000	1.0
log_lik[35,4]	-4.29	2.7e-3	0.17	-4.64	-4.39	-4.28	-4.17	-3.96	4000	1.0

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log_lik[36,4]  -2.71  7.1e-4   0.04   -2.8  -2.73   -2.7  -2.67  -2.62   4000    1.0
log_lik[37,4]  -2.68  6.7e-4   0.04  -2.76   -2.7  -2.67  -2.65   -2.6   4000    1.0
log_lik[38,4]  -2.78  8.1e-4   0.05  -2.89  -2.81  -2.78  -2.74  -2.68   4000    1.0
log_lik[39,4]  -2.71  7.1e-4   0.04   -2.8  -2.73   -2.7  -2.67  -2.62   4000    1.0
log_lik[40,4]  -2.88  9.5e-4   0.06  -3.01  -2.92  -2.88  -2.84  -2.77   4000    1.0
log_lik[41,4]  -3.71  2.0e-3   0.13  -3.97  -3.79   -3.7  -3.62  -3.47   4000    1.0
log_lik[42,4]  -2.71  7.1e-4   0.04   -2.8  -2.73   -2.7  -2.67  -2.62   4000    1.0
log_lik[43,4]  -2.71  7.1e-4   0.04   -2.8  -2.73   -2.7  -2.67  -2.62   4000    1.0
log_lik[44,4]  -3.26  1.4e-3   0.09  -3.44  -3.31  -3.25   -3.2  -3.08   4000    1.0
log_lik[45,4]  -2.71  7.1e-4   0.04   -2.8  -2.73   -2.7  -2.67  -2.62   4000    1.0
log_lik[46,4]  -3.61  1.9e-3   0.12  -3.87  -3.69  -3.61  -3.53  -3.39   4000    1.0
log_lik[47,4]  -2.88  9.5e-4   0.06  -3.01  -2.92  -2.88  -2.84  -2.77   4000    1.0
log_lik[48,4]  -3.61  1.9e-3   0.12  -3.87  -3.69  -3.61  -3.53  -3.39   4000    1.0
log_lik[49,4]  -3.71  2.0e-3   0.13  -3.97  -3.79   -3.7  -3.62  -3.47   4000    1.0
log_lik[50,4]  -2.66  6.5e-4   0.04  -2.75  -2.69  -2.66  -2.64  -2.59   4000    1.0
log_lik[51,4]  -2.71  7.1e-4   0.04   -2.8  -2.73   -2.7  -2.67  -2.62   4000    1.0
log_lik[52,4]  -2.71  7.1e-4   0.04   -2.8  -2.73   -2.7  -2.67  -2.62   4000    1.0
log_lik[53,4]  -3.71  2.0e-3   0.13  -3.97  -3.79   -3.7  -3.62  -3.47   4000    1.0
log_lik[54,4]  -2.65  6.4e-4   0.04  -2.73  -2.68  -2.65  -2.63  -2.58   4000    1.0
log_lik[55,4]  -2.81  8.6e-4   0.05  -2.92  -2.85  -2.81  -2.77  -2.71   4000    1.0
log_lik[56,4]  -2.78  8.1e-4   0.05  -2.89  -2.81  -2.78  -2.74  -2.68   4000    1.0
log_lik[57,4]  -2.73  7.5e-4   0.05  -2.83  -2.76  -2.73   -2.7  -2.64   4000    1.0
log_lik[58,4]  -3.26  1.4e-3   0.09  -3.44  -3.31  -3.25   -3.2  -3.08   4000    1.0
log_lik[59,4]  -2.93  1.0e-3   0.06  -3.06  -2.97  -2.93  -2.89  -2.81   4000    1.0
log_lik[60,4]  -2.78  8.1e-4   0.05  -2.89  -2.81  -2.78  -2.74  -2.68   4000    1.0
log_lik[61,4]  -4.85  3.5e-3   0.22  -5.31  -4.99  -4.84   -4.7  -4.44   4000    1.0
log_lik[62,4]  -3.38  1.6e-3    0.1   -3.6  -3.45  -3.38  -3.32   -3.2   4000    1.0
log_lik[63,4]  -3.61  1.9e-3   0.12  -3.87  -3.69  -3.61  -3.53  -3.39   4000    1.0
log_lik[64,4]  -2.71  7.1e-4   0.04   -2.8  -2.73   -2.7  -2.67  -2.62   4000    1.0
log_lik[65,4]  -2.81  8.6e-4   0.05  -2.92  -2.85  -2.81  -2.77  -2.71   4000    1.0
log_lik[66,4]  -3.47  1.7e-3   0.11  -3.69  -3.53  -3.46   -3.4  -3.26   4000    1.0
ypred[0]       14.08    0.09   5.72   2.95   10.2  14.09  17.87  25.31   4000    1.0
ypred[1]       14.35    0.09   5.68   3.07  10.52  14.26   18.2  25.59   4000    1.0
ypred[2]       13.98    0.09   5.56   3.09  10.25  14.05  17.71  24.85   4000    1.0
ypred[3]       14.53    0.09   5.68   3.53  10.78  14.53  18.29  26.03   3793    1.0
ypred[4]       14.14    0.09   5.65   3.05   10.4  14.09  17.95  25.14   4000    1.0
mu_new         14.17    0.02    0.9  12.32  13.81   14.2  14.57  15.88   2677    1.0
ypred_new      14.21    0.09   5.69   3.31  10.31  14.05  18.16  25.14   4000    1.0
lp__          -754.5    0.07   2.37 -759.8 -756.0 -754.2 -752.8 -750.6   1260    1.0

Samples were drawn using NUTS at Sun Dec  9 13:49:18 2018.
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).
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