# *Appendix for "Differential discrimination against Mobile EU Citizens: Experimental Evidence from bureaucratic choice settings"*

## ***Supplemental Online material***

Technical documentation of the article "Differential discrimination against Mobile EU Citizens: Experimental Evidence from bureaucratic choice settings" for *The Journal of European Public Policy*.

*Contents*

### *Timing of the survey*

Figure 1 shows the temporal evolution of the data collection between late April and mid May 2019.

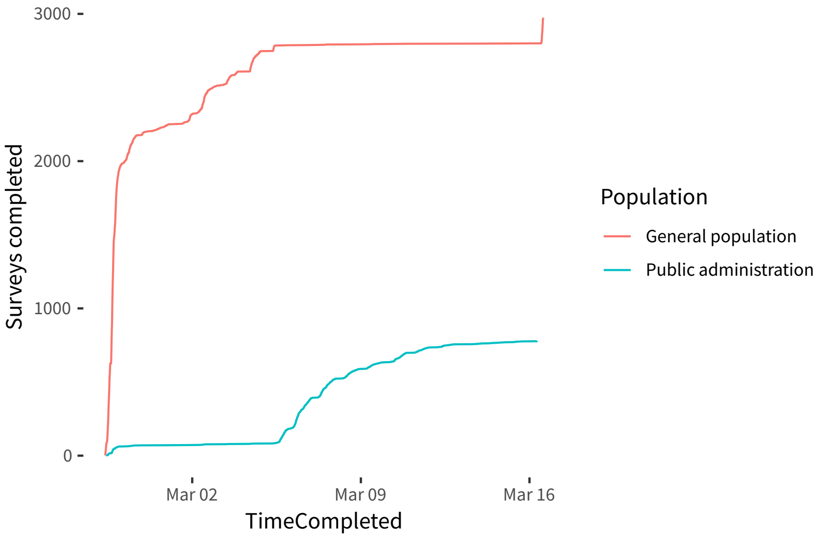



Figure 1: Cumulative distribution of surveys completed over time, by population.

*Time spent reading the assignment*

| Outcome | Treatment | Mean | Median | SD |
|---|---|---|---|---|
| Rights | Not shown | 39.41 | 18.05 | 374.55 |
| Rights | Shown | 35.47 | 19.05 | 181.19 |
| Welfare | Not shown | 21.69 | 16.23 | 33.35 |
| Welfare | Shown | 29.98 | 17.02 | 145.49 |

Table 1: Mean, median and standard deviation of time taken to read the exercises, in a linear scale, by outcome and whether the treatment has been shown.

### *Model specification*

#### *Equation*

Model description:

$$
\begin{aligned}
Y_o &\sim & \mathcal{B}(\pi_o) && \text{Main data component} \\
\pi_o &= & \text{logit}(\theta_{O,p,t,f} F_{o,f}) && \text{Linear relationship} \\
\theta_{O,p,t,f} &\sim & \mathcal{N}(\Theta_{O,f}, \sigma_{\theta_{O,f}}) && \text{Priors for explanatory variables} \\
\Theta_{O,f} &\sim & \mathcal{N}(\Omega_f, \sigma_{\Theta_f}) && \text{Prior for the effects shared by outcome} \\
\sigma_{\theta_{O,f}} &\sim & \mathcal{IG}(1,1) && \text{Prior for SD, pooling of population and treatment} \\
\sigma_{\Theta_f} &\sim & \mathcal{IG}(1,1) && \text{Prior for SD, pooling of outcome} \\
\Omega_f &\sim & \mathcal{N}(0,1) && \text{Prior for the effects of every feature}
\end{aligned}
$$

Where:

- $Y$: Outcome variable capturing whether a profile has been prioritized (1) or not (0).
- $o$: Observation
- $o$: Outcomes (Welfare/ Rights)
- $p$: Population (General population / Public administration)
- $t$: Treatment (Shown / Not shown)
- $F$: Matrix with the observations of Features (the discrimination sources, plus intercept and first shown profile), for each experimental data point.
- $f$: Feature
- $\theta_{O,p,t,f}$: Main parameters of interest capturing the discrimination effects by outcome, population, treatment and profiles' feature.
- $\Theta_{O,f}$: Hyper-parameters capturing the shared effect of outcomes and features over population and treatment.
- $\Omega_f$: Hyper-parameters capturing the shared effect of features over outcomes, population and treatment.
- $\sigma_{\theta_{O,f}}$: Between population/treatment and within outcome/feature standard deviations.
- $\sigma_{\Theta_f}$: Between outcome and within feature standard deviations.

The $\sigma_{\theta_{O,f}}$ can also be seen as a pooling factor. The higher, the more freely are the effects of population and treatment to vary from the overall $\Theta_{O,f}$ shared by outcome and feature. If it is restricted to be very close to 0 then it assumes that there should be a lot of variation from the two populations and two treatments to make them different. Otherwise, they "borrow strength" from the overall means.

We employ weakly informative priors for all parameters, including the pooling factors, to allow all groups to borrow strength from the main effects.

### *Software implementation*

The JAGS code for the model is the following:

```
model {
  for (o in 1:nO) {
    Y[o] ~ dbern(p[o])
    logit(p[o]) <- inprod(theta[id_outcome[o],id_population[o],id_treatment[o],1:nF], X[o,1:nF])
  }
  # Priors for effects
  for (f in 1:nF) {
    for (ocm in 1:nOutcome) {
      for (p in 1:nP) {
        for (t in 1:nT) {
          #theta[ocm,p,t,f] ~ dnorm(Theta[ocm,f], sigma_theta[ocm,f]^-2)
          theta[ocm,p,t,f] ~ dnorm(Theta[ocm,f], tau_theta[ocm,f])
        }
      }
      #sigma_theta[ocm,f] ~ dt(0, 0.5^-2, 1)T(0,)
      tau_theta[ocm,f] ~ dgamma(1, 1)
      sigma_theta[ocm,f] <- 1 / sqrt(tau_theta[ocm,f])
      #Theta[ocm,f] ~ dnorm(Omega[f], sigma_Theta[f]^-2)
      Theta[ocm,f] ~ dnorm(Omega[f], tau_Theta[f])
    }
    #sigma_Theta[f] ~ dt(0, 0.5^-2, 1)T(0,)
    tau_Theta[f] ~ dgamma(1, 1)
    sigma_Theta[f] <- 1 / sqrt(tau_Theta[f])
  }
  Omega ~ dmnorm(b0, B0)
}
```

## *Model comparison: only quality respondents*

Figure 2 shows the comparison of the parameters of the model reported in the article (Baseline) and the model discarding individuals with low quality (less than 4 minutes spent in the completion of the survey or having prioritized the same profile (first or second) for all exercises (12 exercises, 6 in each outcome). Only general population is shown.

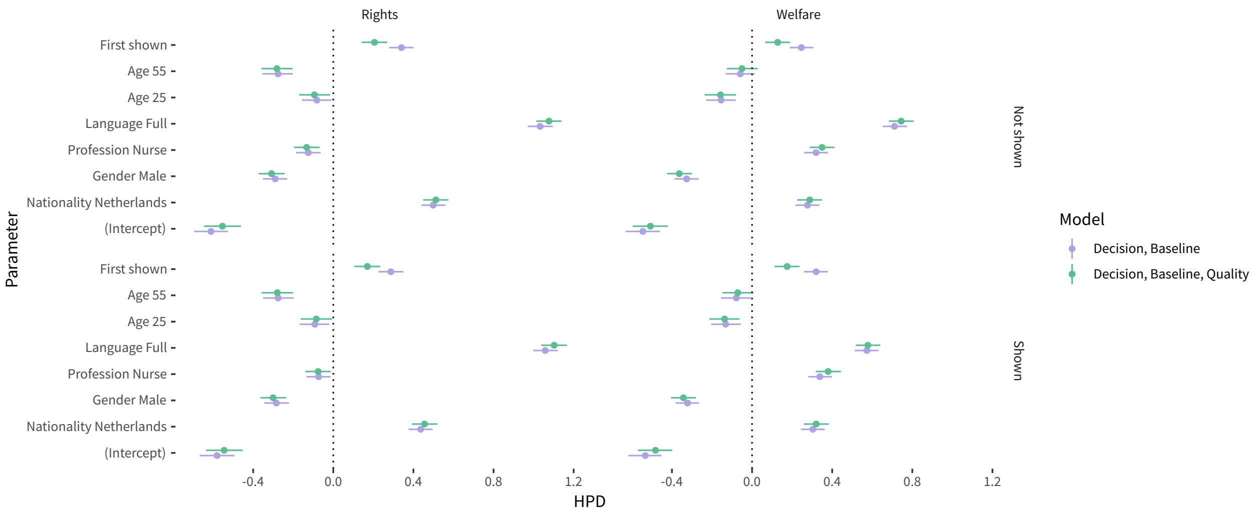



Figure 2: Model comparison. Only general population.

## *Average Marginal Component Effects*

Figure 3 shows the results using the approach in Hainmueller et al. (2014), reporting the Average Marginal Component Effects (AMCE). It replicates the same model than the main one in the article.

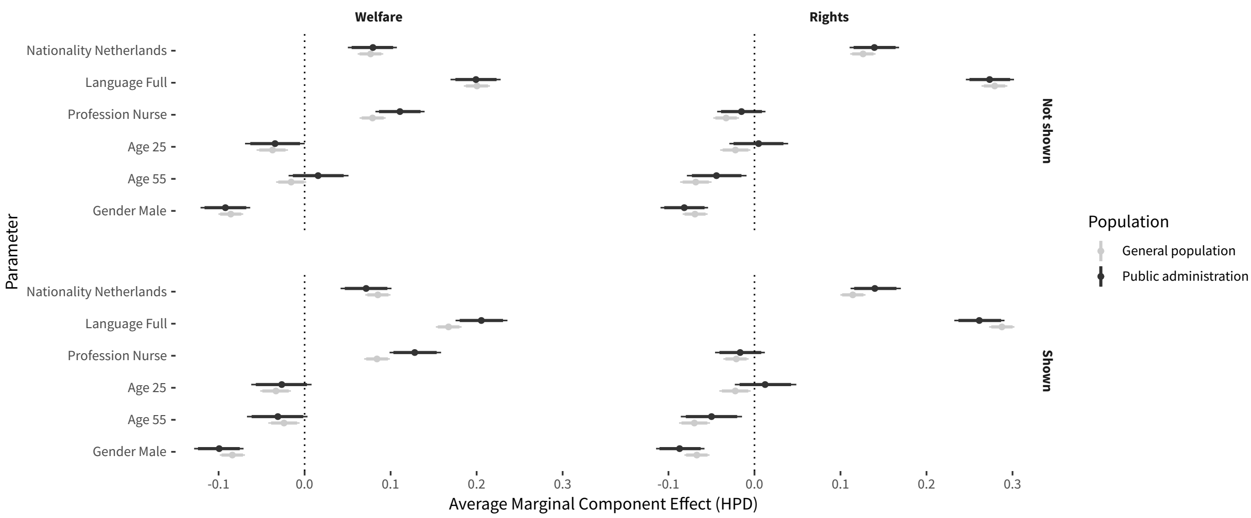
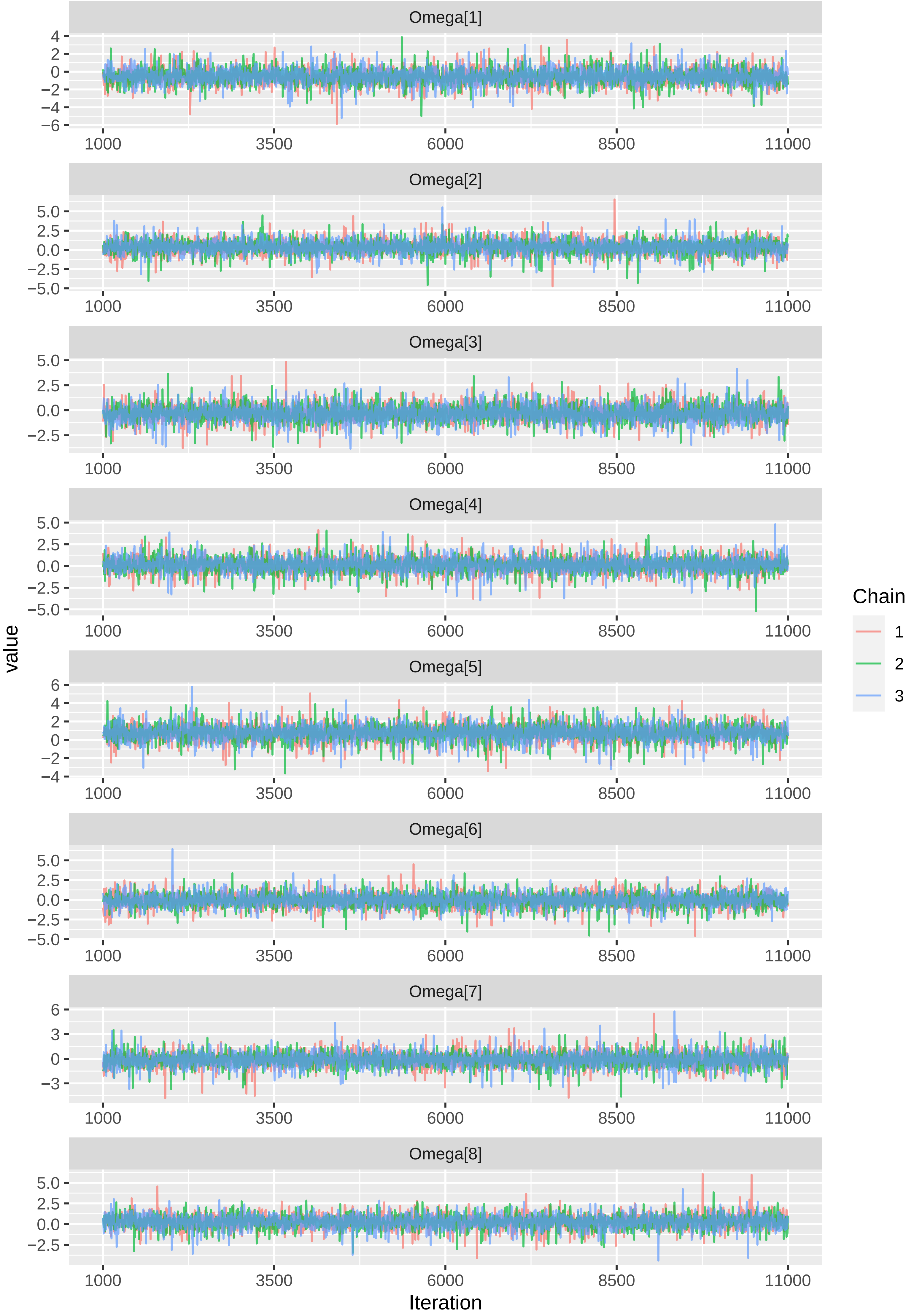



Figure 3: Average Marginal Component Effects.

### *Convergence tests*

After 500 adaptation steps and a burn-in period of 1,000 iterations, we sample 3 chains for 10,000 iterations, thin by 5, and base our results on a total of 6,000 iterations for 112 parameters. Convergence analysis using ggmcmc does not show any traces of non-convergence (Fernández-i-Marín 2016).

This section includes Bayesian convergence tests for the main parameters of interest, namely $\theta$, $\Theta$ and $\Omega$.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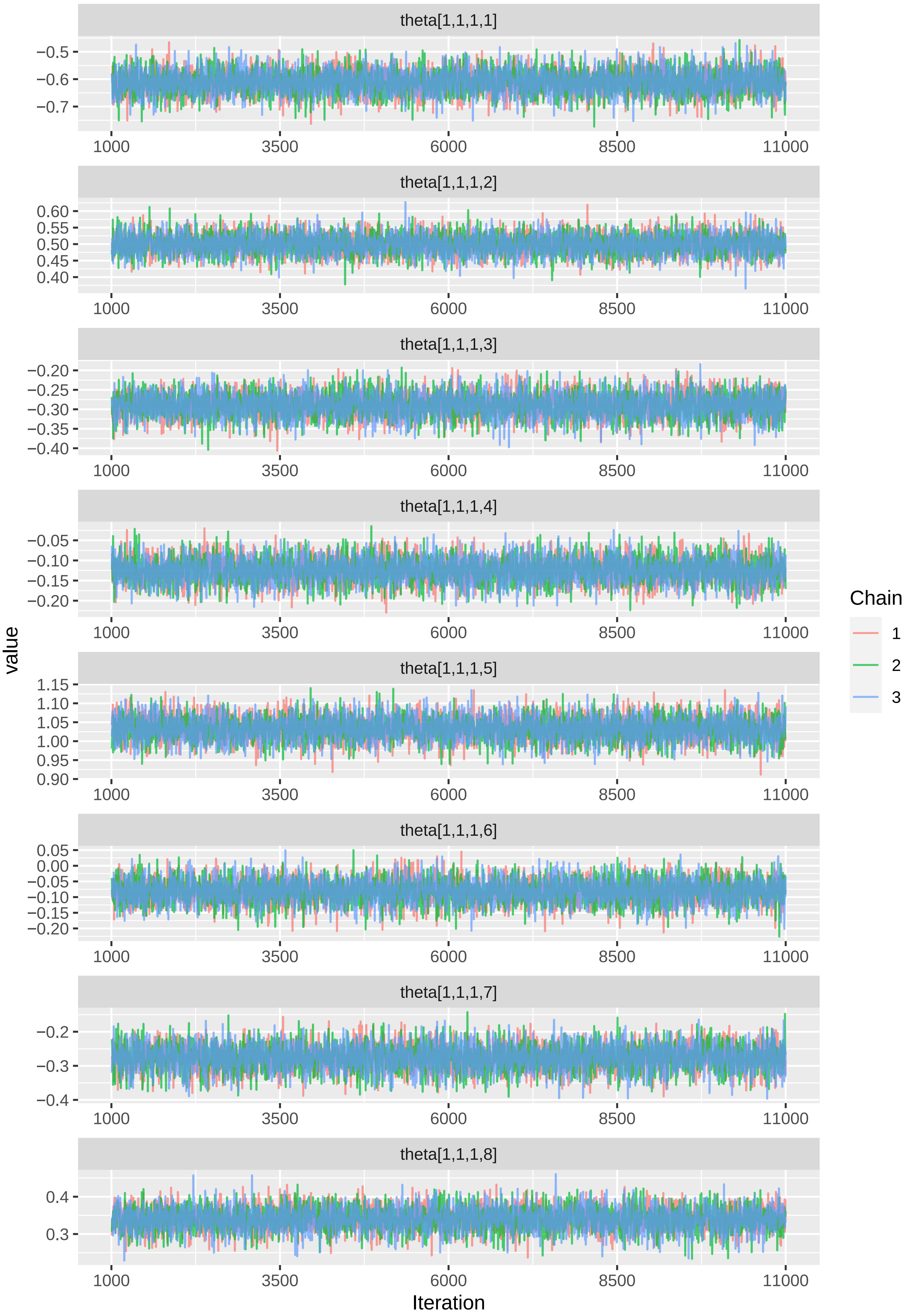
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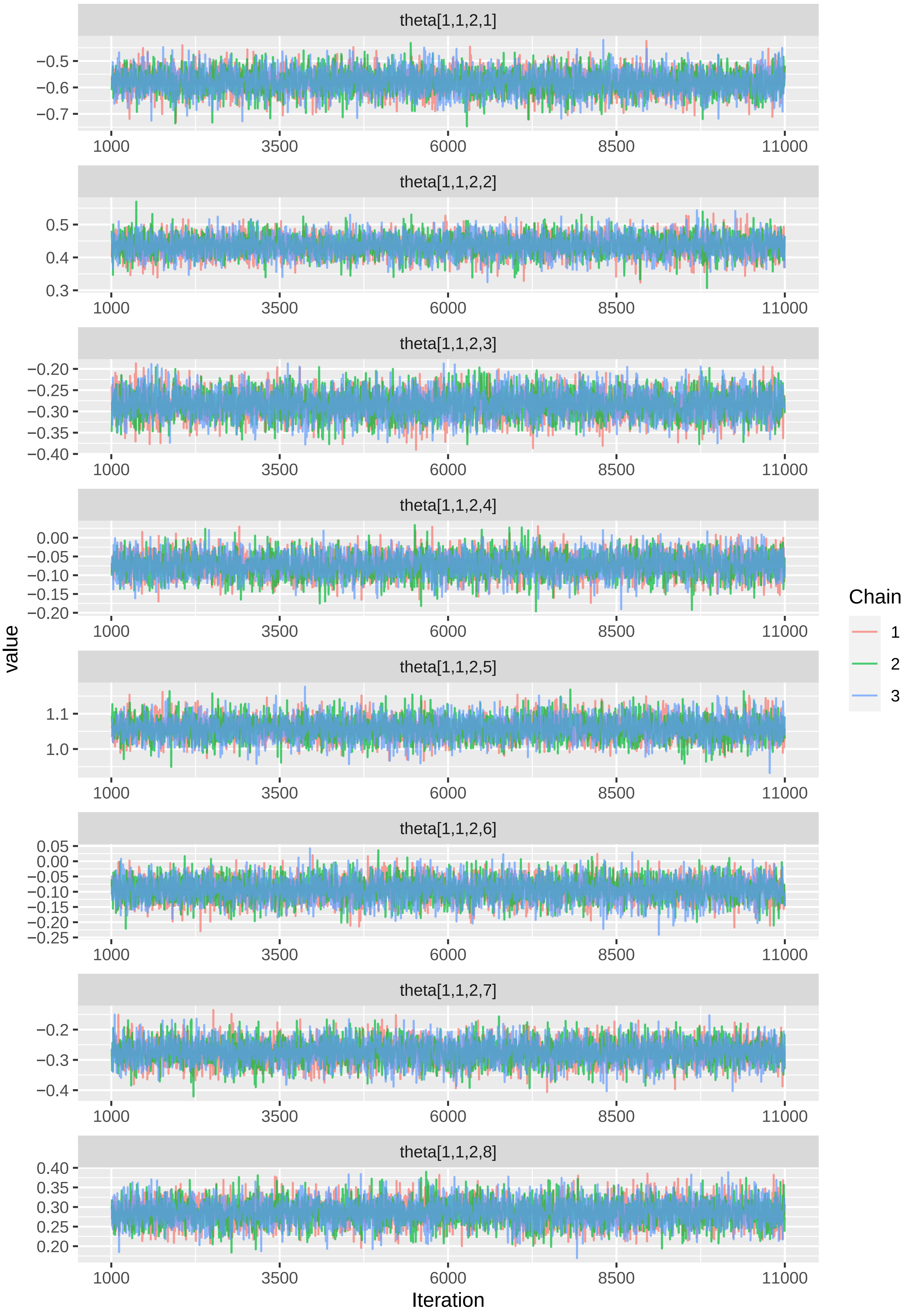
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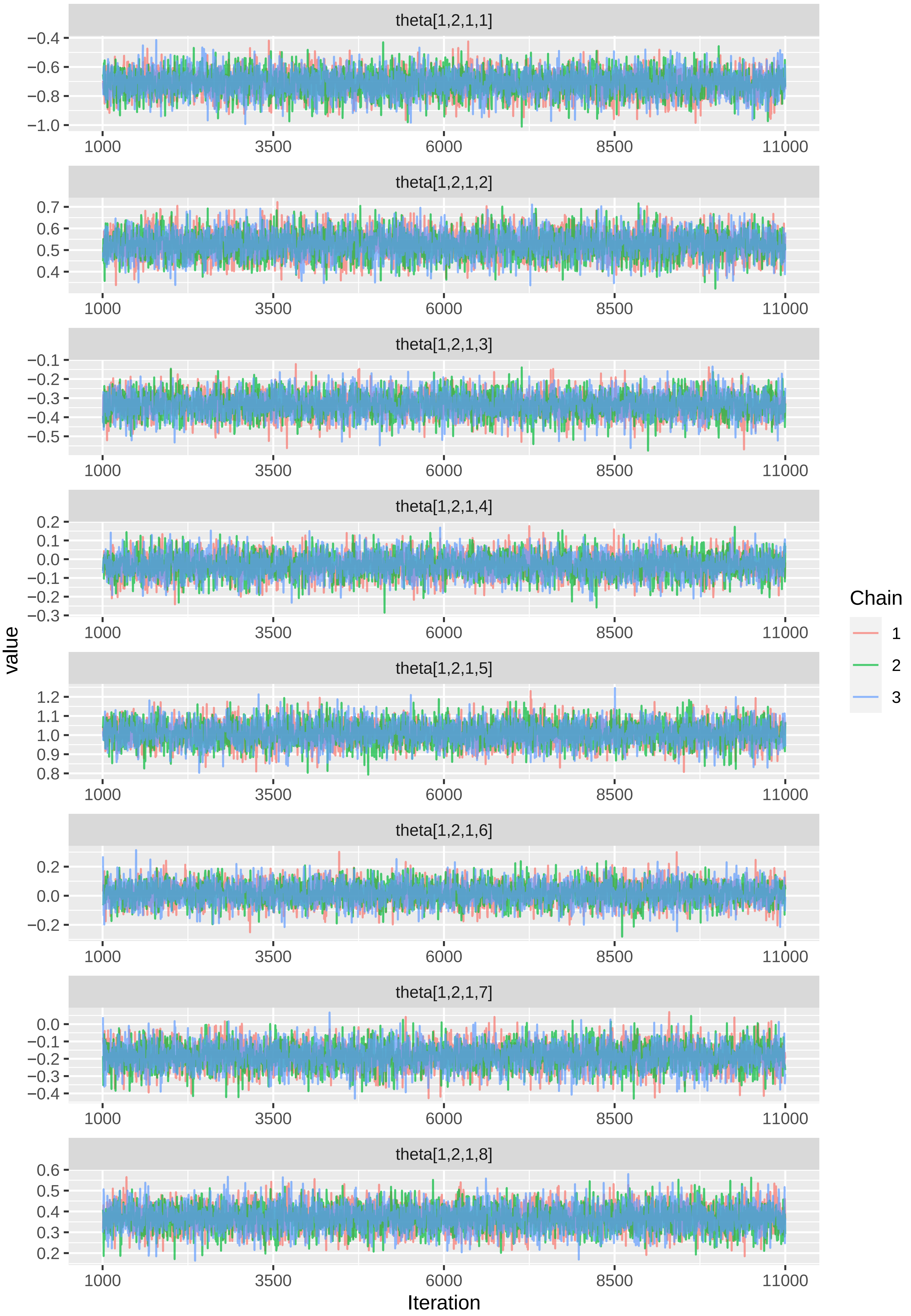
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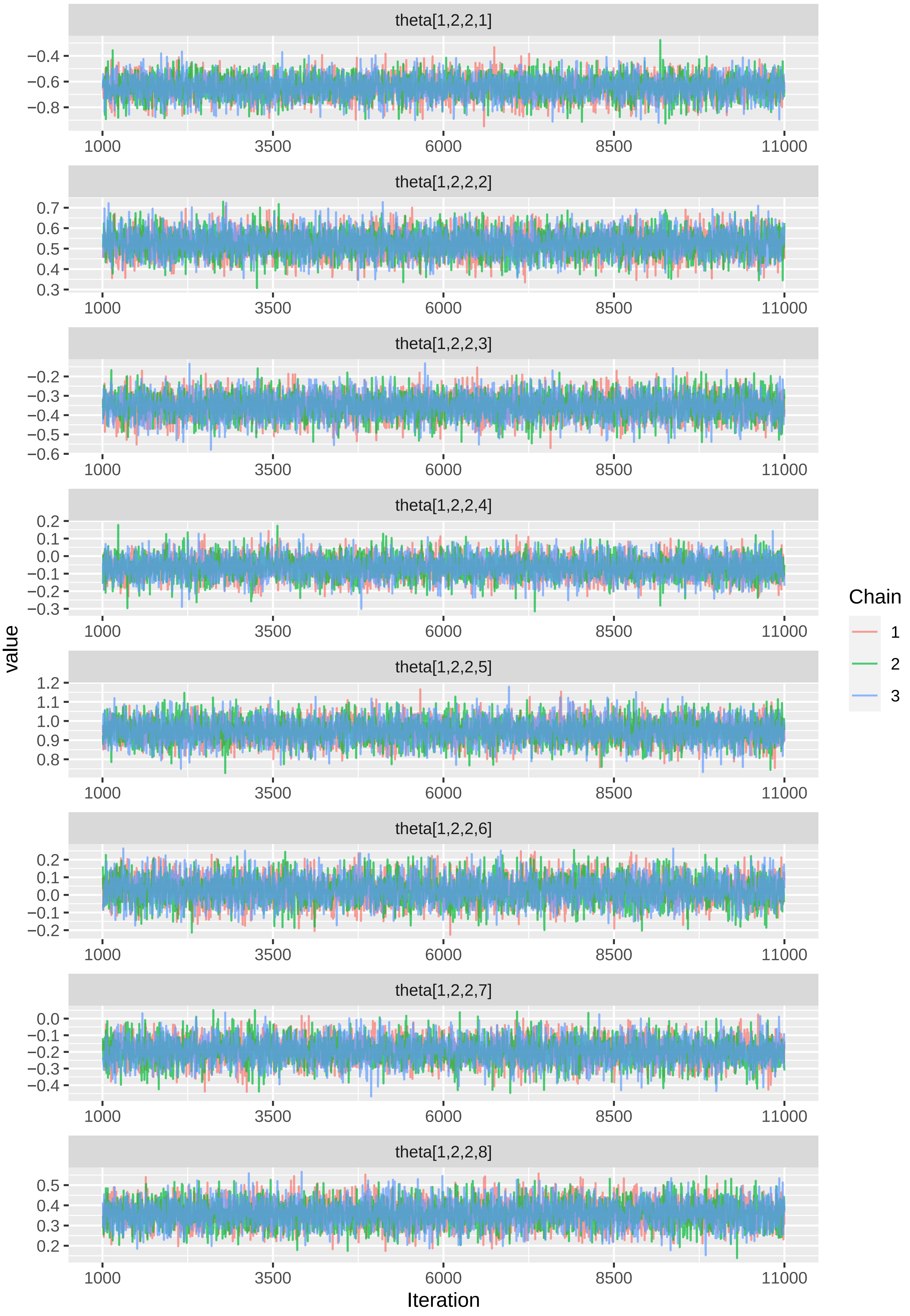
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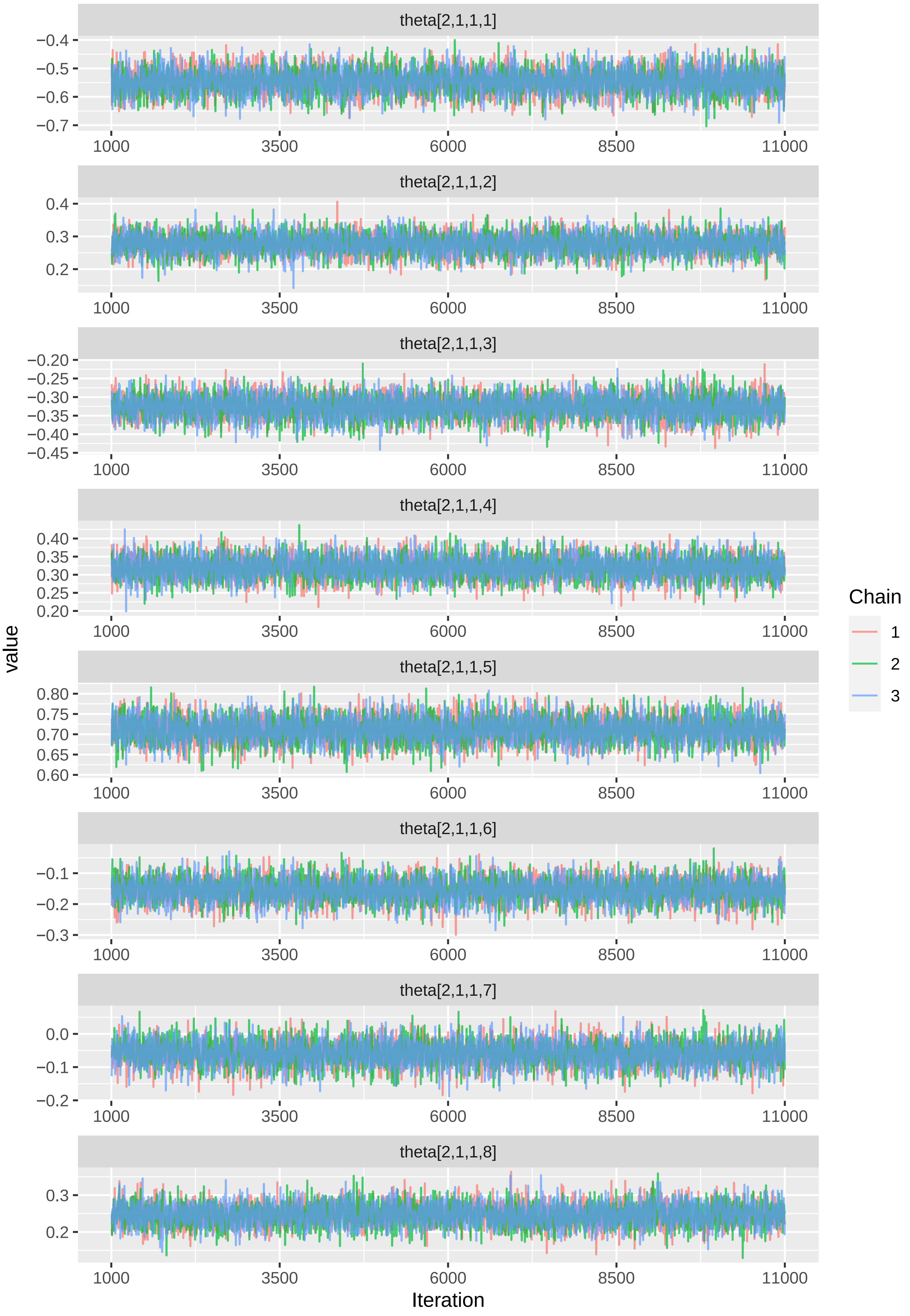
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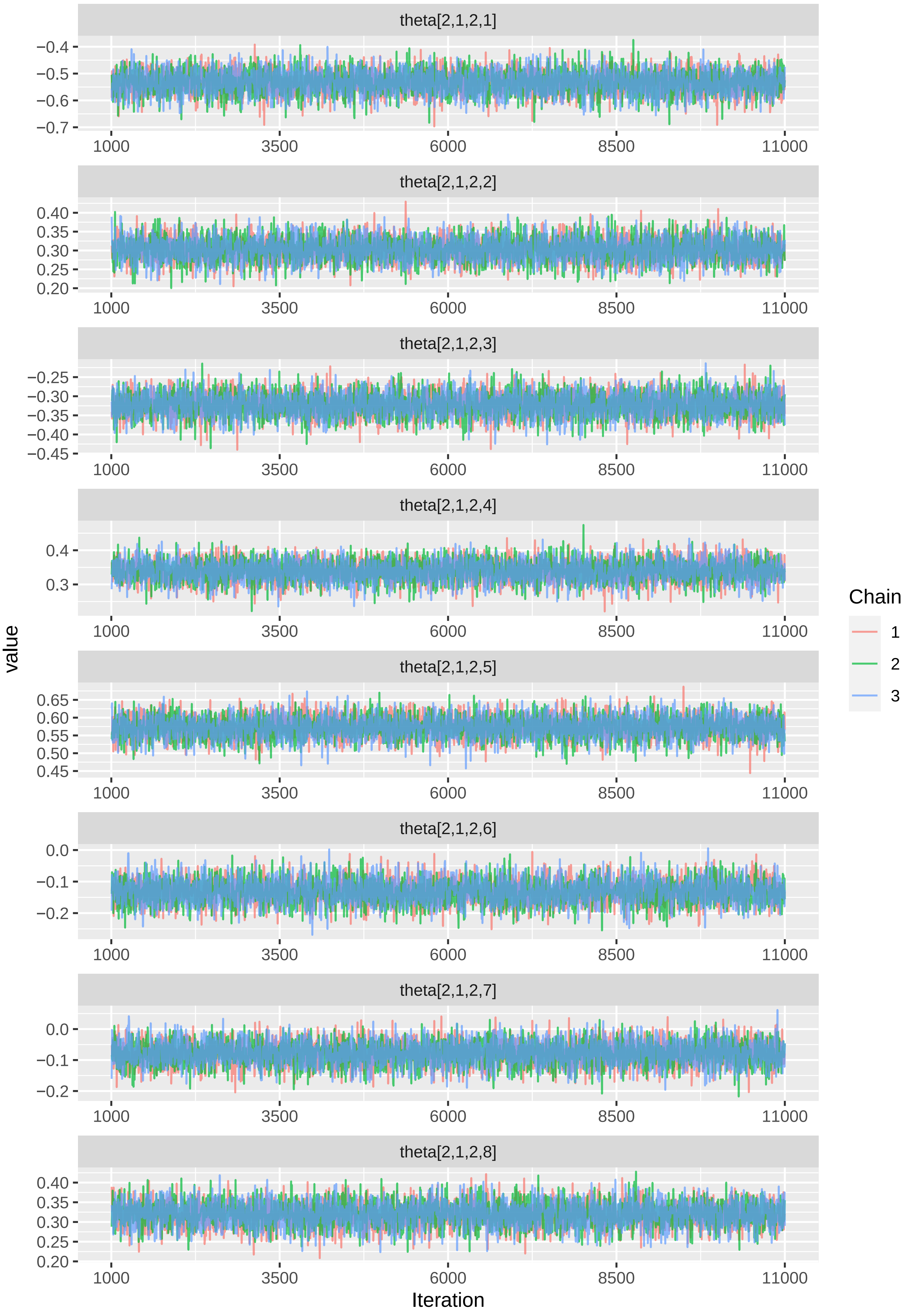
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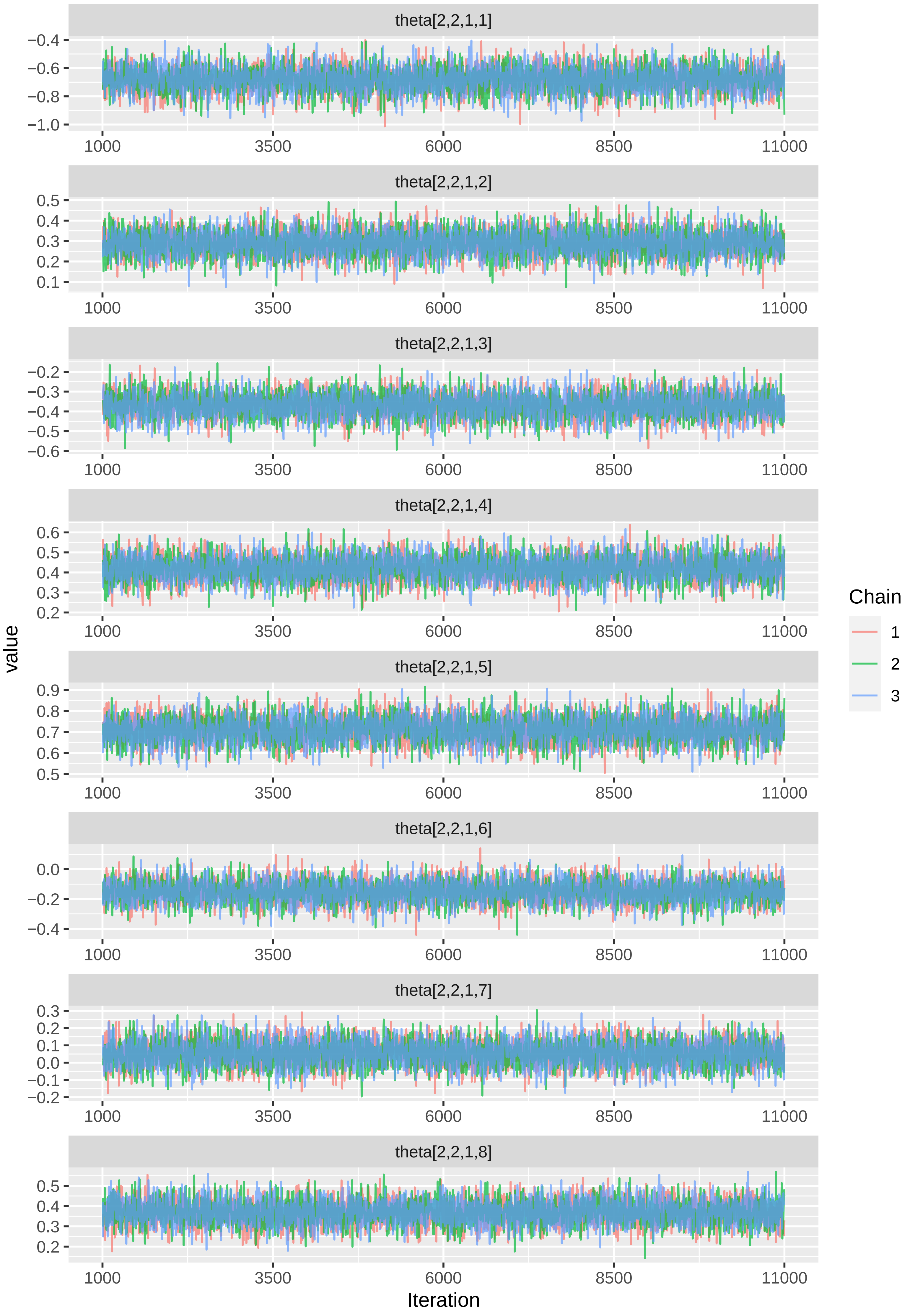

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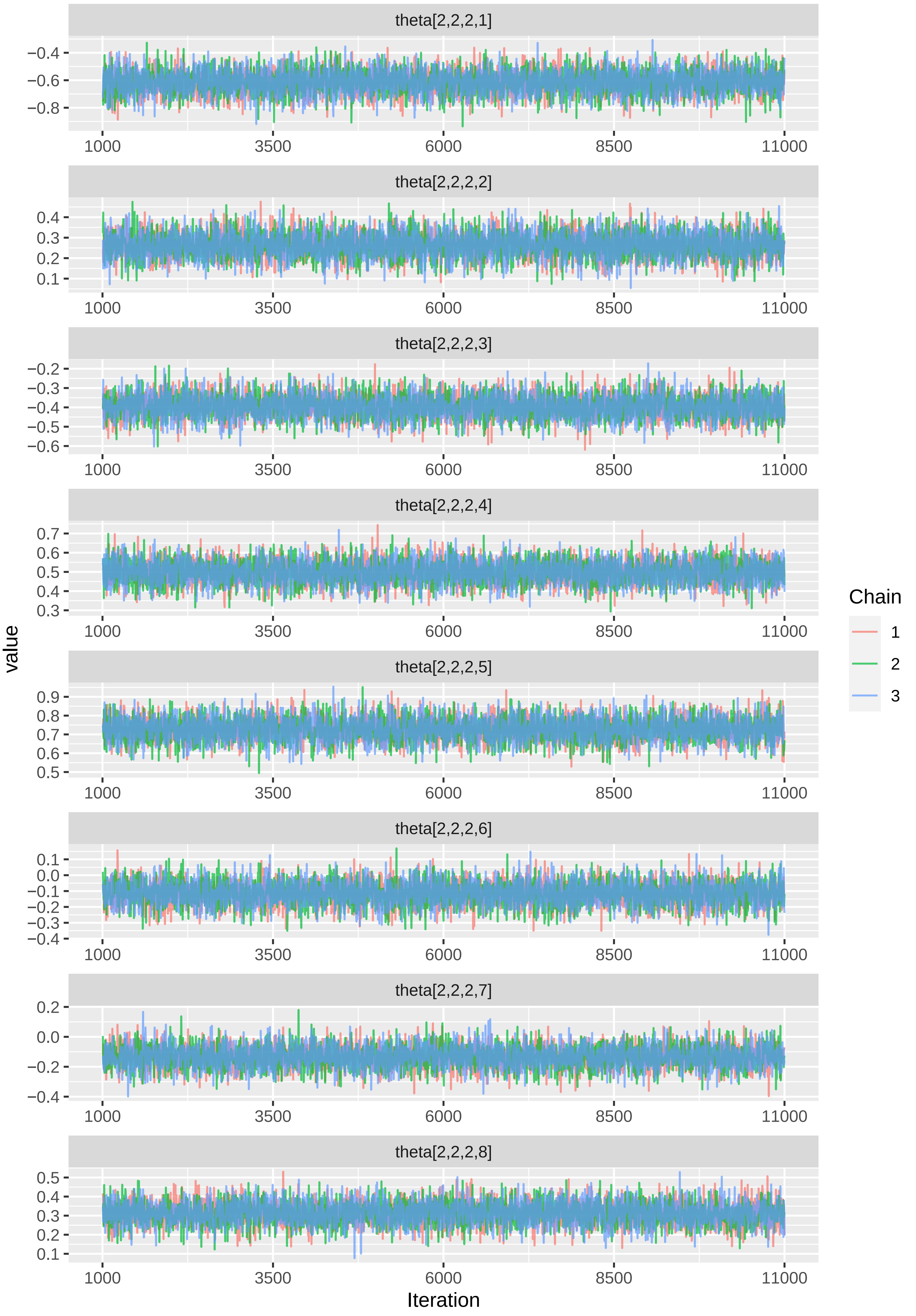
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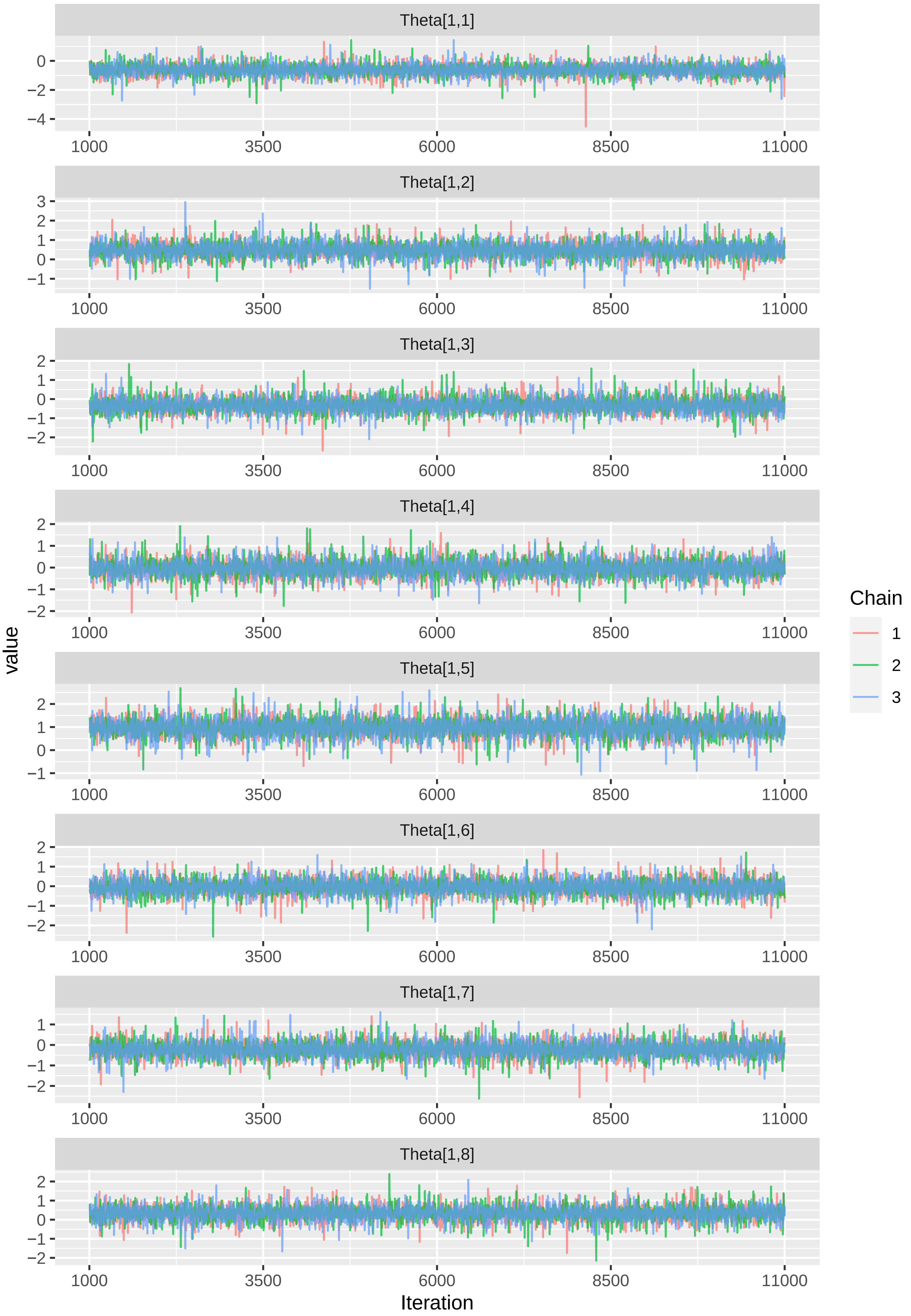

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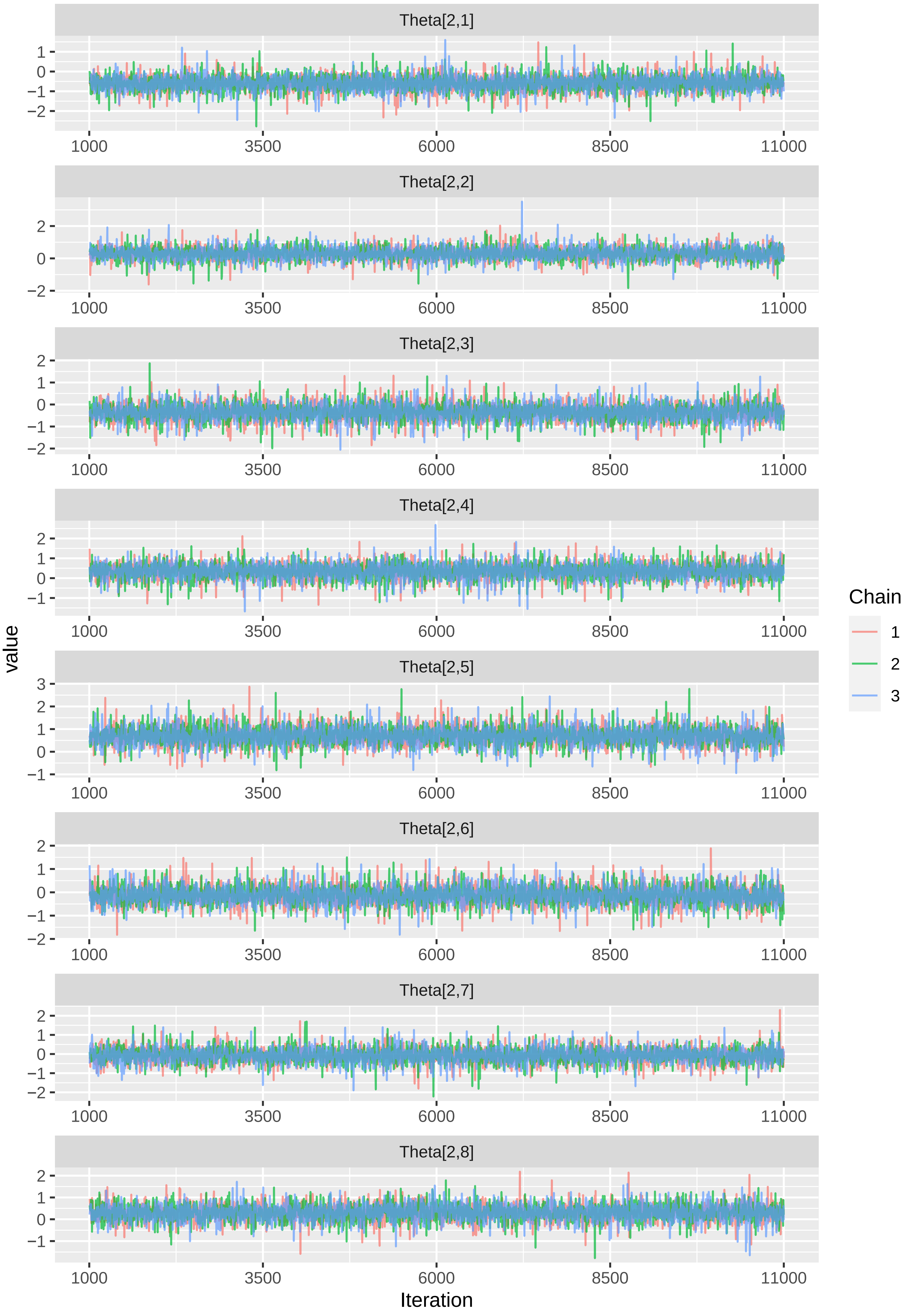
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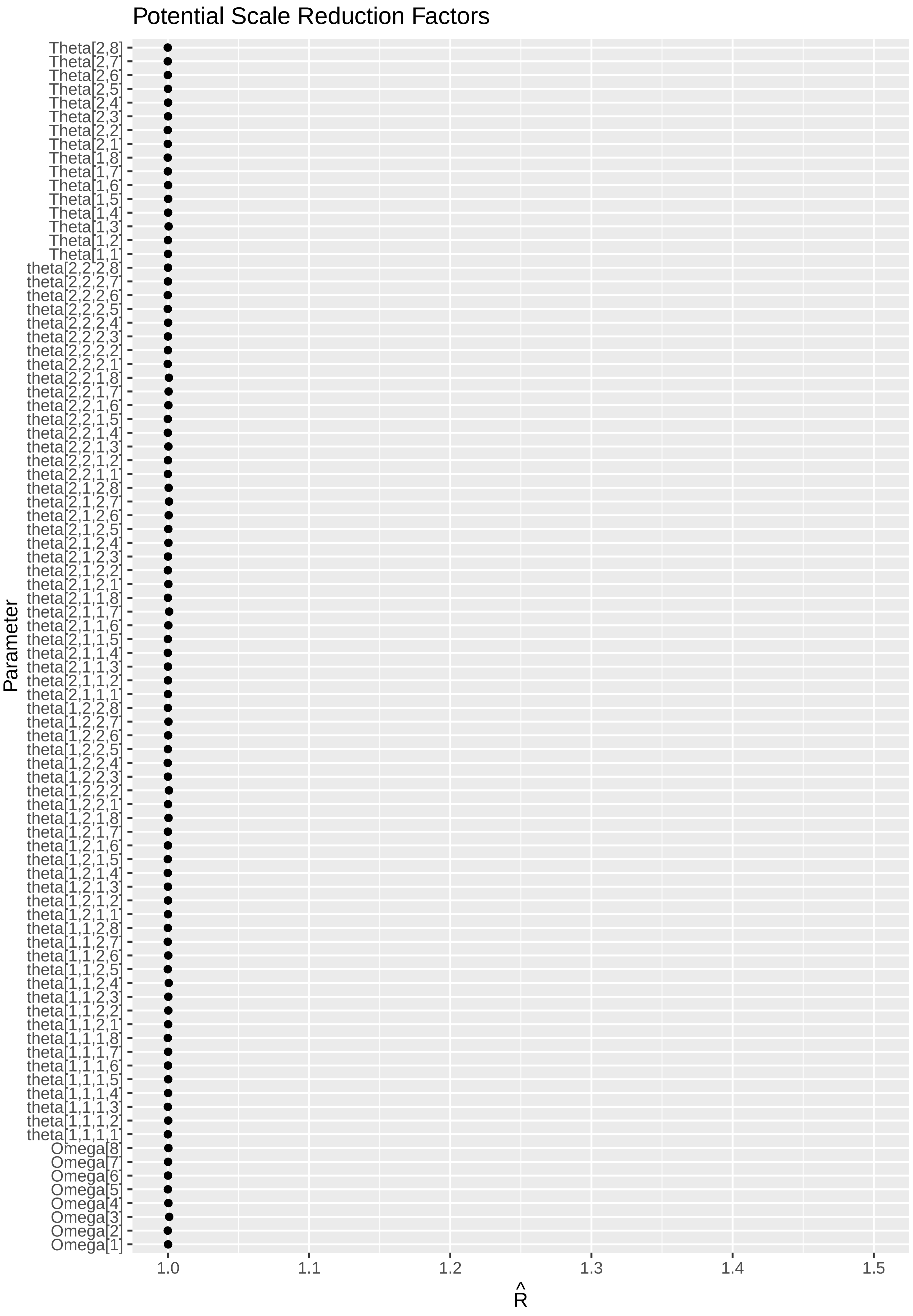

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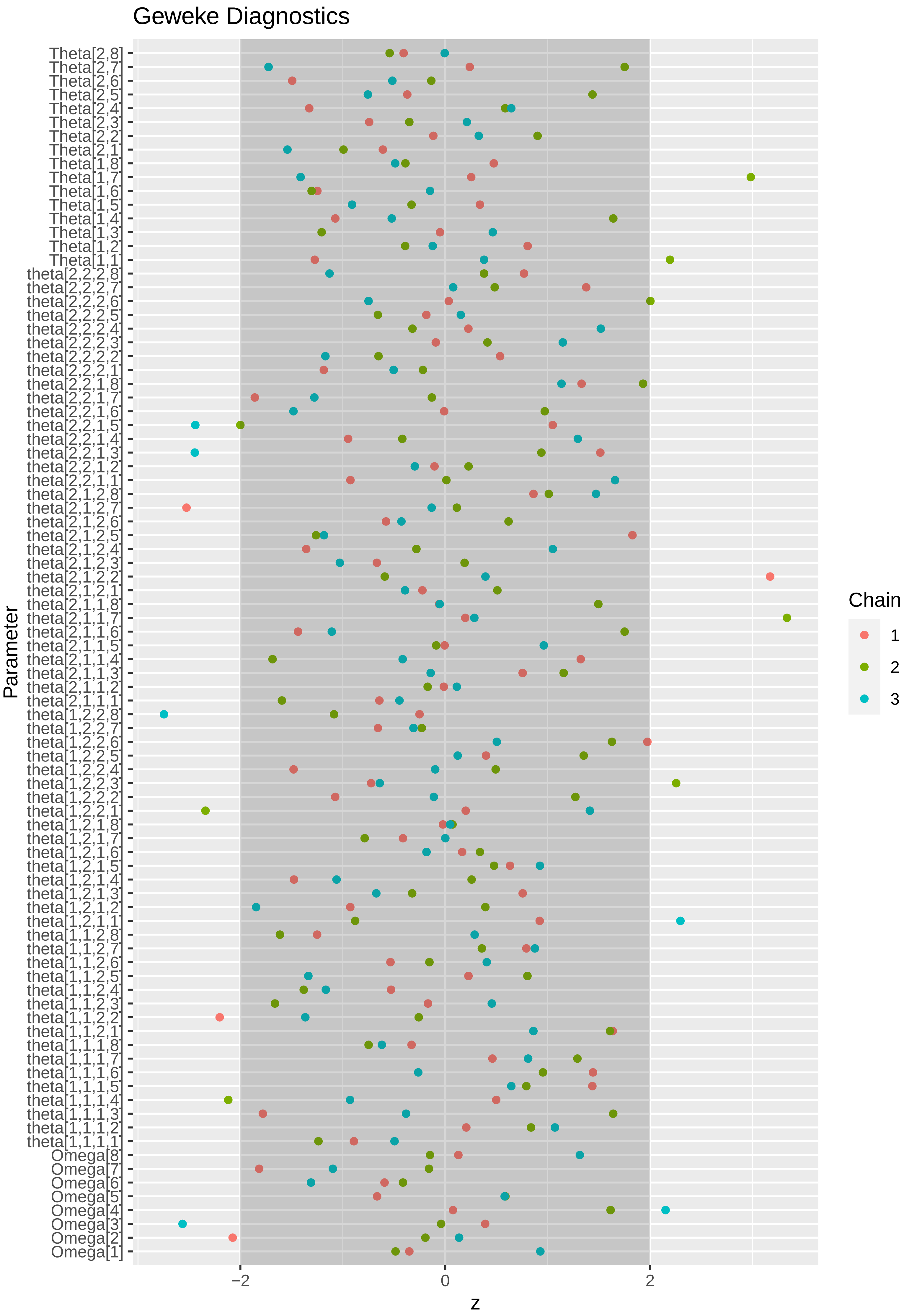

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## *References*

Hainmueller, J., Hopkins, D. J., and Yamamoto, T. (2014). Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments. *Political analysis*, 22(1):1–30.