

**Supplemental material for “Modelling multivariate,  
overdispersed count data with correlated and non-normal  
heterogeneity effects”**

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December 2020

The material contained herein is supplementary to the article named  
in the title and published in SORT-Statistics and Operations  
Research Transactions Volume 44(2).

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## Appendix A

The mean and variance equations in (10) are derived as follows. By letting  $\exp(\mathbf{x}'_{it}\boldsymbol{\beta} + u_{it}) = \mu_{it}\omega_{it}$  an element of vector  $E(Y_i)$  is given by  $E(Y_{it}) = \mu_{it}\mu_{\omega_{it}}$ , where  $\mu_{\omega_{it}} = E(\omega_{it})$ . Using the usual formula to partition variability the variance equals  $\text{var}(Y_{it}) = \mu_{it}^2\sigma_{\omega_{it}} + \mu_{it}\mu_{\omega_{it}}$ . Similarly for  $t \neq s$ ,

$$\begin{aligned} \text{cov}(Y_{it}, Y_{is}) &= E(E(\text{cov}(Y_{it}, Y_{is}|\omega_{it}, \omega_{is}))) \\ &+ \text{cov}(E(E(Y_{it}|\omega_{it})), E(E(Y_{is}|\omega_{is}))) \\ &+ E(\text{cov}(E(Y_{it}|\omega_{it}), E(Y_{is}|\omega_{is}))). \end{aligned}$$

It is straightforward to show that the first part is 0, the second part equals  $\text{cov}(\mu_{it}\mu_{\omega_{it}}, \mu_{is}\mu_{\omega_{is}}) = 0$ , and the last part is  $E(\text{cov}(\mu_{it}\omega_{it}, \mu_{is}\omega_{is})) = \mu_{it}\mu_{is}\sigma_{\omega_{ts}}$ . Reorganizing terms leads to (10).

## Appendix B

**McMC PSN.** For the PSN model, after some algebra, we derive the following complete conditional posteriors

$$\begin{aligned} i) \beta|\mathbf{y}, \text{others} &\sim N_k\left(\mathbf{C}_\beta\left\{\sigma^{-2}\sum_{i=1}^n \mathbf{X}'_i(\boldsymbol{\theta}_i - \delta\mathbf{z}_i) + \mathbf{V}_\beta^{-1}\boldsymbol{\beta}_0\right\}, \mathbf{C}_\beta\right), \\ ii) \sigma^2|\mathbf{y}, \text{others} &\sim IG\left(\frac{nT}{2} + \nu_0, \frac{1}{2}\sum_{i=1}^n \sum_{t=1}^T (\theta_{it} - \mathbf{x}'_{it}\boldsymbol{\beta} - \delta z_{it})^2 + \nu_0\right), \\ iii) \delta|\mathbf{y}, \text{others} &\sim N\left(\frac{c_\delta}{\sigma_\delta^{-2} + \sigma^{-2}\sum_{i=1}^n \sum_{t=1}^T z_{it}^2}, \frac{1}{\sigma_\delta^{-2} + \sigma^{-2}\sum_{i=1}^n \sum_{t=1}^T z_{it}^2}\right), \\ iv) z_{it}|\mathbf{y}, \text{others} &\stackrel{\text{ind}}{\sim} TN\left(\frac{\delta(\theta_{it} - \mathbf{x}'_{it}\boldsymbol{\beta})}{\sigma^2 + \delta^2}, \frac{\sigma^2}{\sigma^2 + \delta^2}\right)I(0, \infty), \\ v) \pi(\theta_{it}|\mathbf{y}, \text{others}) &\propto e^{-e^{\theta_{it}} - \frac{1}{2\sigma^2}[\theta_{it} - (\mathbf{x}'_{it}\boldsymbol{\beta} - \delta z_{it} + \sigma^2 y_{it})]^2}, \end{aligned}$$

where  $\mathbf{C}_\beta = \left(\sigma^{-2}\sum_{i=1}^n \mathbf{X}'_i\mathbf{X}_i + \mathbf{V}_\beta^{-1}\right)^{-1}$ ,  $c_\delta = \sigma_\delta^{-2}\delta_0 + \sigma^{-2}\sum_{i=1}^n \sum_{t=1}^T z_{it}(\theta_{it} - \mathbf{x}'_{it}\boldsymbol{\beta})$ ,  $\mathbf{X}_i = (\mathbf{x}_{i1}, \mathbf{x}_{i2}, \dots, \mathbf{x}_{in})'$  and  $\mathbf{y} = (\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_n)'$  with  $\mathbf{y}_i = (\mathbf{y}_{i1}, \mathbf{y}_{i2}, \dots, \mathbf{y}_{iT})'$ . It is seen that all conditional posteriors, except for  $\theta_{it}$ , are analytically in closed forms of known distributions and thus simulation is easy. To generate  $\theta_{it}$  for subject  $i = 1, \dots, n$  and at time  $t = 1, \dots, T$ , a Metropolis-within-Gibbs algorithm, which is available in the OpenBugs software, is used.

The Gibbs sampling to fit mixed Poisson models with multivariate skew-normal mixing priors are given as follow.

- **McMC PMSN1.** Using the hierarchical form for PMSN1 and adopting the priors, we derive the related complete conditional posteriors as follow

$$\begin{aligned} i) \beta|\mathbf{y}, \text{others} &\sim N_k\left(\mathbf{C}_\beta\left\{\sum_{i=1}^n \mathbf{X}'_i\mathbf{V}^{-1}(\boldsymbol{\theta}_i - \delta\mathbf{z}_i) + \mathbf{V}_\beta^{-1}\boldsymbol{\beta}_0\right\}, \mathbf{C}_\beta\right), \\ ii) \mathbf{V}|\mathbf{y}, \text{others} &\sim IW_T(\mathbf{C}_\mathbf{V}, n+m), \\ iii) \delta|\mathbf{y}, \text{others} &\sim N\left(\mathbf{C}_\delta(\mathbf{V}_\delta^{-1}\boldsymbol{\delta}_0 + \sum_{i=1}^n z_i\mathbf{V}^{-1}(\boldsymbol{\theta}_i - \mathbf{X}_i\boldsymbol{\beta})), \mathbf{C}_\delta\right), \\ iv) z_i|\mathbf{y}, \text{others} &\sim TN\left(\frac{\boldsymbol{\delta}'\mathbf{V}^{-1}(\boldsymbol{\theta}_i - \mathbf{X}_i\boldsymbol{\beta})}{\boldsymbol{\delta}'\mathbf{V}^{-1}\boldsymbol{\delta} + 1}, \frac{1}{\boldsymbol{\delta}'\mathbf{V}^{-1}\boldsymbol{\delta} + 1}\right)I(0, \infty), \\ v) \pi(\boldsymbol{\theta}_i|\mathbf{y}, \text{others}) &\propto \left\{\prod_{t=1}^T e^{-e^{\theta_{it}} + \theta_{it}y_{it}}\right\} e^{-\frac{1}{2}c_\theta\boldsymbol{\theta}_i}, \end{aligned}$$

where  $\mathbf{C}_\delta = (\mathbf{V}_\delta^{-1} + \mathbf{V}^{-1} \sum_{i=1}^n z_i^2)^{-1}$ ,  $c_{\theta_i} = (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \delta z_i)' \mathbf{V}^{-1} (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \delta z_i)$ ,  $\mathbf{C}_\mathbf{V} = \boldsymbol{\Omega} + \sum_{i=1}^n (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \delta z_i) (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \delta z_i)'$ , and  $\mathbf{C}_\beta = \left( \sum_{i=1}^n \mathbf{X}_i' \mathbf{V}^{-1} \mathbf{X}_i + \mathbf{V}_\beta^{-1} \right)^{-1}$ , and  $\mathbf{X}_i = (\mathbf{x}_{i1}, \mathbf{x}_{i2}, \dots, \mathbf{x}_{iT})'$ .

- **McMC PMSN2.** Using the hierarchical form for PMSN2 and adopting similar priors given in PMSN1 for  $\boldsymbol{\beta}$  and  $\boldsymbol{\delta}$ ,  $IW_T(\boldsymbol{\Omega}_\varepsilon, m_\varepsilon)$  for matrix  $\mathbf{V}_\varepsilon$ , the inverse-Gamma  $IG(\gamma, \gamma)$  for the variance component  $\sigma_\alpha^2$ , the complete conditional posteriors are derived as

$$\begin{aligned}
i) & \boldsymbol{\beta} | \mathbf{y}, \text{others} \sim N_k(\mathbf{d}_\beta, \mathbf{C}_\beta), \\
ii) & \mathbf{V}_\varepsilon | \mathbf{y}, \text{others} \sim IW_T(\mathbf{C}_{\mathbf{V}_\varepsilon}, n + m_\varepsilon), \\
iii) & \sigma_\alpha^2 | \mathbf{y}, \text{others} \sim IG\left(\frac{n}{2} + \gamma, \frac{1}{2} \sum_{i=1}^n \alpha_i^2 + \gamma\right), \\
iv) & \boldsymbol{\delta} | \mathbf{y}, \text{others} \sim N_T(\mathbf{d}_\delta, \mathbf{C}_\delta), \\
v) & z_i | \mathbf{y}, \text{others} \sim TN\left(\frac{c_{z_i}}{\boldsymbol{\delta}' \mathbf{V}_\varepsilon^{-1} \boldsymbol{\delta} + 1}, \frac{1}{\boldsymbol{\delta}' \mathbf{V}_\varepsilon^{-1} \boldsymbol{\delta} + 1}\right) I(0, \infty), \\
vi) & \alpha_i | \mathbf{y}, \text{others} \sim N\left(\frac{\mathbf{1}_T' \mathbf{V}_\varepsilon^{-1} (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \delta z_i)}{\mathbf{1}_T' \mathbf{V}_\varepsilon^{-1} \mathbf{1}_T + \sigma_\alpha^{-2}}, \frac{1}{\mathbf{1}_T' \mathbf{V}_\varepsilon^{-1} \mathbf{1}_T + \sigma_\alpha^{-2}}\right), \\
vii) & \pi(\boldsymbol{\theta}_i | \mathbf{y}, \text{others}) \propto \left\{ \prod_{t=1}^T e^{-e^{\theta_{it}} + \theta_{it} y_{it}} \right\} e^{-\frac{1}{2} c_{\theta_i}},
\end{aligned}$$

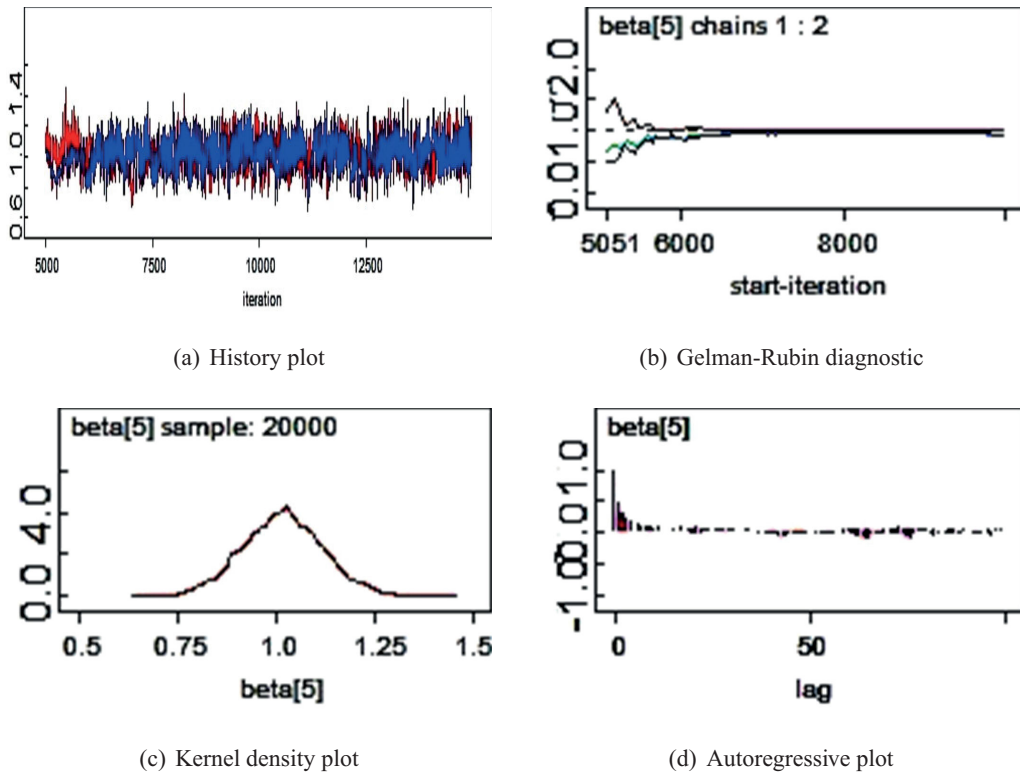
where  $\mathbf{C}_\beta = \left( \sum_{i=1}^n \mathbf{X}_i' \mathbf{V}_\varepsilon^{-1} \mathbf{X}_i + \mathbf{V}_\beta^{-1} \right)^{-1}$ ,  $\mathbf{C}_\delta = (\mathbf{V}_\delta^{-1} + \mathbf{V}_\varepsilon^{-1} \sum_{i=1}^n z_i^2)^{-1}$ ,  $c_{z_i} = \boldsymbol{\delta}' \mathbf{V}_\varepsilon^{-1} (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \alpha_i \mathbf{1}_T)$ ,  $c_{\theta_i} = (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \delta z_i - \alpha_i \mathbf{1}_T)' \mathbf{V}_\varepsilon^{-1} (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \delta z_i - \alpha_i \mathbf{1}_T)$ ,  $\mathbf{d}_\beta = \mathbf{C}_\beta \left\{ \sum_{i=1}^n \mathbf{X}_i' \mathbf{V}_\varepsilon^{-1} (\boldsymbol{\theta}_i - \delta z_i - \alpha_i \mathbf{1}_T) + \mathbf{V}_\beta^{-1} \boldsymbol{\beta}_0 \right\}$ ,  $\mathbf{d}_\delta = \mathbf{C}_\delta (\mathbf{V}_\delta^{-1} \boldsymbol{\delta}_0 + \sum_{i=1}^n z_i \mathbf{V}_\varepsilon^{-1} (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \alpha_i \mathbf{1}_T))$ , and  $\mathbf{C}_{\mathbf{V}_\varepsilon} = \boldsymbol{\Omega}_\varepsilon + \sum_{i=1}^n (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \delta z_i - \alpha_i \mathbf{1}_T) (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \delta z_i - \alpha_i \mathbf{1}_T)'$ .

- **McMC PMSN3.** Using the hierarchical form for PMSN3 and letting the underlying priors being similar to those given in model PMSN2 except that for  $\boldsymbol{\delta}$  the prior  $\boldsymbol{\delta} \sim N(\boldsymbol{\delta}_0, \sigma_\delta^2)$  is replaced. The complete conditional posteriors are derived as

$$\begin{aligned}
i) & \boldsymbol{\beta} | \mathbf{y}, \text{others} \sim N_k\left(\mathbf{C}_\beta \left\{ \sum_{i=1}^n \mathbf{X}_i' \mathbf{V}_\varepsilon^{-1} (\boldsymbol{\theta}_i - \alpha_i \mathbf{1}_T) + \mathbf{V}_\beta^{-1} \boldsymbol{\beta}_0 \right\}, \mathbf{C}_\beta\right), \\
ii) & \mathbf{V}_\varepsilon | \mathbf{y}, \text{others} \sim IW_T(\mathbf{C}_{\mathbf{V}_\varepsilon}, n + m_\varepsilon) \\
iii) & \sigma_\alpha^2 | \mathbf{y}, \text{others} \sim IG\left(\frac{n}{2} + \gamma, \frac{1}{2} \sum_{i=1}^n (\alpha_i - \delta z_i)^2 + \gamma\right). \\
iv) & \delta | \mathbf{y}, \text{others} \sim N\left(\frac{\frac{\sigma_\delta^2 \delta_0 + \sigma_\alpha^{-2} \sum_{i=1}^n z_i \alpha_i}{\sigma_\delta^{-2} + \sigma_\alpha^{-2} \sum_{i=1}^n z_i^2}}{\frac{\sigma_\delta^{-2} + \sigma_\alpha^{-2} \sum_{i=1}^n z_i^2}{\sigma_\delta^{-2} + \sigma_\alpha^{-2} \sum_{i=1}^n z_i^2}}, \frac{1}{\sigma_\delta^{-2} + \sigma_\alpha^{-2} \sum_{i=1}^n z_i^2}\right), \\
v) & z_i | \mathbf{y}, \text{others} \sim TN\left(\frac{\delta \alpha_i}{\sigma_\alpha^2 + \delta^2}, \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \delta^2}\right) I(0, \infty), \\
vi) & \alpha_i | \mathbf{y}, \text{others} \sim N\left(\frac{c_{\alpha_i}}{\mathbf{1}_T' \mathbf{V}_\varepsilon^{-1} \mathbf{1}_T + \sigma_\alpha^{-2}}, \frac{1}{\mathbf{1}_T' \mathbf{V}_\varepsilon^{-1} \mathbf{1}_T + \sigma_\alpha^{-2}}\right), \\
vii) & \pi(\boldsymbol{\theta}_i | \mathbf{y}, \text{others}) \propto \left\{ \prod_{t=1}^T e^{-e^{\theta_{it}} + \theta_{it} y_{it}} \right\} e^{-\frac{1}{2} c_{\theta_i}},
\end{aligned}$$

where  $\mathbf{C}_\beta = \left( \sum_{i=1}^n \mathbf{X}_i' \mathbf{V}_\varepsilon^{-1} \mathbf{X}_i + \mathbf{V}_\beta^{-1} \right)^{-1}$ ,  $c_{\theta_i} = (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \alpha_i \mathbf{1}_T)' \mathbf{V}_\varepsilon^{-1} (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \alpha_i \mathbf{1}_T)$ ,  $c_{\alpha_i} = \mathbf{1}_T' \mathbf{V}_\varepsilon^{-1} (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta}) + \sigma_\alpha^{-2} \delta z_i$  and  $\mathbf{C}_{\mathbf{V}_\varepsilon} = \boldsymbol{\Omega}_\varepsilon + \sum_{i=1}^n (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \alpha_i \mathbf{1}_T) (\boldsymbol{\theta}_i - \mathbf{X}_i \boldsymbol{\beta} - \alpha_i \mathbf{1}_T)'$ .

**Posterior plots in the health reform data analysis:** Figure 1 shows the history, Gelman-Rubin diagnostic, kernel density, and autocorrelation plots for the PMSN2 and  $\beta_5$ . By using two different sequences of starting points, the Gelman-Rubin diagnostic plot shows the same behaviour. Also, we observe a low correlation between successive samples in the autocorrelation plot. Moreover, the history plot moves up and down around the mode of the distribution. Thus the samples will reach a stationary distribution.



*Figure 1: The posterior plots of  $\beta_5$  in the simulation study.*