A Description of the PX-HC algorithm

Let $N = \sum_{c=1}^{C} N_c$ and write $\sum_{c=1}^{C}\sum_{i=1}^{N_c}\sum_{k=1}^{K_{ci}}$ as $\sum_{c,i,k}$, the Gibbs sampling algorithm at iteration m for continuous outcomes:

Step A: For $j = 1, ..., J$, draw $\boldsymbol{\theta}^{(m)}$ in the following steps:

A1.

$$\lambda_j^{*(m)} \sim \mathrm{N}\left(\boldsymbol{\Omega}_{\lambda_j}\sum_{c,i,k}\Big[y_{cikj}^{c} - W_{cik}^{T}\boldsymbol{\beta}_j^{(m-1)} - \xi_j^{(m-1)} b_{cij}^{*(m-1)}\Big]\frac{U_{cik}^{*(m-1)}}{\sigma_j^{2(m-1)}}, \boldsymbol{\Omega}_{\lambda_j}\right)\mathbf{1}_{\{\lambda_j^{*(m)}\geq 0\}},$$

where $\boldsymbol{\Omega}_{\lambda_j} = \left[\sum_{c,i,k}\frac{U_{cik}^{*2(m-1)}}{\sigma_j^{2(m-1)}} + 1\right]^{-1}$.

A2.

$$\boldsymbol{\beta}_j^{(m)} \sim N\left(\boldsymbol{\Omega}_{\boldsymbol{\beta}_j}\sum_{c,i,k}\Big[y_{cikj}^{c} - \lambda_j^{*(m)} U_{cik}^{*(m-1)} - \xi_j^{(m-1)} b_{cij}^{*(m-1)}\Big]\frac{W_{cik}}{\sigma_j^{2(m-1)}}, \boldsymbol{\Omega}_{\boldsymbol{\beta}_j}\right),$$

where $\boldsymbol{\Omega}_{\boldsymbol{\beta}_j} = \left(\frac{1}{\sigma_j^{2(m-1)}}\sum_{c,i,k} W_{cik}W_{cik}^{T} + \Sigma_{\boldsymbol{\beta}}^{-1}\right)^{-1}$, and $\Sigma_{\boldsymbol{\beta}} = 1000\ \mathbf{I}_{p_1}$ is the prior variance for $\boldsymbol{\beta}_j$.

A3.

$$\xi_j^{(m)} \sim N\left(\boldsymbol{\Omega}_{\xi_j}\sum_{c,i,k}\Big[y_{cikj}^{c} - W_{cik}^{T}\boldsymbol{\beta}_j^{(m)} - \lambda_j^{*(m)} U_{cik}^{*(m-1)}\Big]\frac{b_{cij}^{*(m-1)}}{\sigma_j^{2(m-1)}}, \boldsymbol{\Omega}_{\xi_j}\right),$$

where $\boldsymbol{\Omega}_{\xi_j} = \left(\sum_{c,i}\frac{K_{ci} b_{cij}^{*2(m-1)}}{\sigma_j^{2(m-1)}} + 1\right)^{-1}$

A4.

$$\begin{aligned}
\psi^{2(m)} &\sim IG(A_1^{(m)}, A_2^{(m)}),\ \text{where } A_1^{(m)} = \frac{\sum_{c=1}^{C}\sum_{i=1}^{N_c} K_{ci}}{2} + \frac{1}{2},\ \text{and} \\
A_2^{(m)} &= \frac{1}{2}\sum_{c,i}\left(A_{ci}^{(m)T} H_{ci}^{-1}(\rho^{(m-1)}) A_{ci}^{(m)}\right) + \frac{1}{2}, \\
A_{ci}^{(m)} &= \mathbf{U}_{ci}^{*(m-1)} - \mu^{*(m-1)} 1_{K_{ci}} - X_{ci}\alpha^{*(m-1)} - \mathbf{1}_{K_{ci}} g_c^{*(m-1)} - Z_{ci} \bigotimes \mathbf{1}_{K_{ci}} a_c^{*(m-1)}.
\end{aligned}$$

A5.

$$\alpha^{*(m)} \sim N\left(\mu_\alpha, \boldsymbol{\Omega}_\alpha\right),$$

where

$$\mu_\alpha = \sum_{c,i} X_{ci}^T H_{ci}^{-1}(\rho^{(m-1)}) \left(\mathbf{U}_{ci}^{*(m-1)} - \mu^{*(m-1)} 1_{K_{ci}} - Z_{ci} \bigotimes 1_{K_{ci}} a_c^{*(m-1)} - g_c^{*(m-1)} \mathbf{1}_{K_{ci}} \right)$$
$$\times \quad \mathbf{\Omega}_\alpha \frac{1}{\psi^2},$$

$\mathbf{\Omega}_\alpha = \left(\frac{1}{\psi^2} \sum_{c,i} X_{ci}^T H_{ci}^{-1}(\rho^{(m-1)}) X_{ci} + \Sigma_\alpha^{-1} \right)^{-1}.$

A6.

$$\mu^* \sim N(\mu_\mu, \Omega_\mu),$$

where

$$\mu_\mu = \sum_{c,i} \left(\mathbf{U}^{*(m-1)} - X_{ci}\alpha^{*(m)} - g_c^{*(m-1)} \mathbf{1}_{K_{ci}} - Z_{ci} \bigotimes \mathbf{1}_{K_{ci}} a_c^{*(m-1)} \right)^T H_{ci}^{-1}(\rho^{(m-1)}) \mathbf{1}_{K_{ci}}$$
$$\times \quad \frac{\Omega_\mu}{\psi^2},$$

and $\Omega_\mu = \left[\frac{1}{\psi^2} \sum_{c,i} \mathbf{1}_{K_{ci}} H_{ci}^{-1} \mathbf{1}_{K_{ci}} + \frac{1}{1000} \right]$.

A7. For $j = 1, ..., J$,

$$\mu_{bj}^{*(m)} \sim N\left(\left(\sum_{c=1}^{C} \sum_{i=1}^{N_c} \frac{b_{cij}^{*(m-1)}}{(\tau_j^{*(m-1)})^2} \right) \left(\frac{N}{(\tau_j^{*(m-1)})^2} + \frac{1}{1000} \right)^{-1}, \left(\frac{N}{(\tau_j^{*(m-1)})^2} + \frac{1}{1000} \right)^{-1} \right).$$

A8. For $j = 1, ..., J$,

$$\tau_j^{*2(m)} \sim IG\left(\frac{N}{2} + \frac{1}{2}, \frac{1}{2} \sum_{c=1}^{C} \sum_{i=1}^{N_c} (b_{cij}^{*(m-1)} - \mu_{bj}^{*(m)})^2 + \frac{1}{2} \right).$$

A9.

$$\sigma_g^{*2} \sim IG\left(\frac{C}{2} + 0.1, \frac{\sum_{c=1}^{C} (g_c^{*(m-1)})^2}{2} + 0.1 \right).$$

A10.

$$\sigma_a^{*2} \sim IG\left(\frac{N}{2} + 0.1, \sum_{c=1}^{C} \frac{(a_c^{*(m-1)})^T a_c^{*(m-1)}}{2} + 0.1 \right).$$

A11. For $j = 1, ..., J$,

$$\sigma_j^{2(m)} \sim IG\left(\frac{\sum_{c=1}^{C} \sum_{i=1}^{N_c} K_{ci}}{2} + 0.1, \frac{1}{2} \sum_{c,i,k} \left(y_{cikj}^c - W_{cik}^T \boldsymbol{\beta}_j^{(m)} - \lambda_j^{*(m)} U_{cik}^{*(m-1)} - \xi_j^{(m)} b_{cij}^{*(m-1)} \right)^2 + 0.1 \right)$$

A12.

$$p(\rho^{(m)}|....) \propto \prod_{c=1}^{C} \prod_{i=1}^{N_c} |H_{ci}(\rho)|^{-1/2} \exp\left\{ -\frac{1}{2\psi^2} \sum_{c=1}^{C} \sum_{i=1}^{N_c} A_{ci}^{(m)T} H_{ci}^{-1}(\rho) A_{ci}^{(m)} \right\}.$$

where

$$A_{ci}^{(m)} = \mathbf{U}_{ci}^{(m-1)} - \mu^* - X_{ci}\alpha^{(m)} - g_c^{(m-1)}\mathbf{1}_{K_{ci}} - Z_{ci} \bigotimes \mathbf{1}_{T_{ci}} a_c^{(m-1)},$$

and $H_{ci}(\rho)$ is a $K_{ci} \times K_{ci}$ matrix with $(r,k)^{th}$ element $\rho^{|t_{cir}-t_{cik}|}$. We use parameter transformation to transform ρ to η via $\eta = log(\frac{\rho}{1-\rho})$. Then the conditional distribution for posterior η is:

$$p(\eta|...) \propto \prod_{c=1}^{C}\prod_{i=1}^{N_c} |H_{ci}(\rho(\eta))|^{-1/2} \exp\left\{-\frac{1}{2\psi^2}\sum_{c=1}^{C}\sum_{i=1}^{N_c} A_{ci}^{(m)T} H_{ci}^{-1}(\rho(\eta)) A_{ci}^{(m)}\right\} \frac{\exp(\eta)}{(1+exp(\eta))^2},$$

where $\rho(\eta) = \frac{exp(\eta)}{1+exp(\eta)}$. Random walk Metropolis-Hastings algorithm is used to sample η with proposal $N(\eta_{old}, v^2)$, where v^2 is tuned to have a reasonable acceptance rate.

Step B Sample all latent variables:

B1. For each $\{c,i\}$, $\mathbf{U_{ci}^{(m)}} \sim \mathbf{MVN}(\mu_{\mathbf{U_{ci}}}, \mathbf{\Omega_{U_{ci}}})$ with

$$\begin{aligned} \mu_{U_{ci}} &= \Omega_{U_{ci}} \left[\sum_{j=1}^{J} \frac{\lambda_j^{*(m)}}{\sigma_j^{2(m)}} (\mathbf{y}_{cij}^c - \mathbf{W}_{ci}\beta_j^{(m)} - \xi_j^{(m)} b_{cij}^{(m)} \mathbf{1}_{K_{ci}})\right] \\ &+ \Omega_{U_{ci}} \frac{1}{\psi^2}\left[\mu^{*(m)} + X_{ci}\alpha^{*(m)} + g_c^{*(m-1)} 1_{K_{ci}} + Z_{ci} \bigotimes 1_{K_{ci}} a_c^{*(m-1)}\right]^T H_{ci}^{-1}(\rho^{(m)}) \end{aligned}$$

and $\Omega_{U_{ci}} = \left(\sum_{j=1}^{J} \frac{\lambda_j^{*2(m)}}{\sigma_j^{2(m)}} I_{K_{ci}} + \frac{1}{\psi^2} H_{ci}^{-1}(\rho^{(m)})\right)^{-1}$.

B2. For each $\{c,i\}$ draw

$$b_{cij}^{*(m)} \sim N\left(\Omega_{b_{cij}}\left[\sum_{t=1}^{K_{ci}} \frac{\xi_j^{(m)}}{\sigma_j^{2(m)}} (y_{cikj}^c - W_{cik}^T \boldsymbol{\beta}_j^{(m)} - \lambda_j^{*(m)} U_{cik}^{*(m)}) + \frac{\beta_{0j}^{*(m)}}{(\tau_j^{*(m)})^2}\right], \Omega_{b_{cij}}\right),$$

where $\Omega_{b_{cij}} = \left(\frac{K_{ci}\xi_j^{2(m)}}{\sigma_j^{2(m)}} + \frac{1}{(\tau_j^{*(m)})^2}\right)^{-1}$.

B3. For each c, $g_c^* \sim N(\mu_{g_c}, \Omega_{g_c})$ with

$$\mu_{g_c} = \frac{\Omega_{g_c}}{\psi^2} \sum_{i=1}^{N_c} \left(\mathbf{U_{ci}^{*(m)}} - \mu^{*(\mathbf{m})} \mathbf{1_{K_{ci}}} - \mathbf{X_{ci}} \alpha^{*(\mathbf{m})} - \mathbf{Z_{ci}} \bigotimes \mathbf{1_{T_{ci}}} \mathbf{a_c^{*(m-1)}}\right)^T H_{ci}^{-1}(\rho^{(m)}) \mathbf{1}_{T_{ci}},$$

and $\Omega_{g_c} = \left(\frac{1}{\psi^2}\sum_{i=1}^{N_c} \mathbf{1}_{T_{ci}} H_{ci}^{-1}(\rho^{(m)}) \mathbf{1}_{T_{ci}} + \frac{1}{\sigma_g^{*2}}\right)^{-1}$.

B4. For $c = 1, ...C$, For each c, $a_c^{*(m)} \sim MVN(\mu_{a_c}, \Omega_{a_c})$ with

$$\mu_{a_c} = \frac{\Omega_{a_c}}{\psi^2} \sum_{i=1}^{N_c} \left(Z_{ci} \bigotimes 1_{T_{ci}} \right)^T H_{ci}^{-1}(\rho^{(m)}) \left(\mathbf{U_{ci}^{*(m)}} - \mu^{*(\mathbf{m})} \mathbf{1_{K_{ci}}} - \mathbf{X_{ci}} \alpha^{*(\mathbf{m})} - \mathbf{g_c^{*(m)}} \mathbf{1_{T_{ci}}} \right),$$

and $\Omega_{a_c} = \left(\frac{1}{\psi^2} \sum_{i=1}^{N_c} (Z_{ci} \bigotimes 1_{T_{ci}})^T H_{ci}^{-1}(\rho^{(m)}) (Z_{ci} \bigotimes 1_{T_{ci}}) + \frac{1}{\sigma_a^{*2(m)}} I_{N_c} \right)^{-1}$.

B Description of the PX^2-HC algorithm

The following steps are used to produce the sampling updates:

Step C For all parameters that determine the continuous response and latent variable, the Gibbs steps are identical to the ones described in the previous section. Specifically, the conditional distributions used in the Gibbs updates are identical for $\{(\lambda_j^*, \boldsymbol{\beta}_j, \xi_j, b_{cij}^*, \sigma_j^2) : 1 \le j \le J_1\}$, ψ, $\boldsymbol{\alpha}^*$, $\boldsymbol{a}^*$, g^*, μ^*, $\boldsymbol{\mu_b}^*$, σ_a^{*2}, σ_g^{*2}, $\boldsymbol{\tau}^{*2}$, ρ)

Step D For $j = J_1 + 1, \ldots, J$ the following conditional distributions are used to update the chain

D1. Draw

$$y_{cikj}^{b*(m)} \sim \begin{cases} TN_+(\mu_{cikj}^*, 1), & \text{if } y_{cikj}^b = 1 \\ TN_-(\mu_{cikj}^*, 1), & \text{if } y_{cikj}^b = 0 \end{cases},$$

where $TN_+(\mu, \sigma^2)$ and $TN_-(\mu, \sigma^2)$ are truncated normals with mean μ and variance σ^2 truncated to $(0, \infty)$ and $(-\infty, 0)$, respectively. Also $\mu_{cikj}^* = W_{cik}^T \boldsymbol{\beta}_j^{(m)} + \lambda_j^{*(m)} U_{cik}^{*(m)} + \xi_j^{(m)} b_{cij}^{*(m)}$. Put $\widetilde{y}_{cikj}^{b*(m)} = \gamma_j^{(m-1)} y_{cikj}^{b*(m)}$.

D2.

$$\gamma_j^{2(m)} \sim IG\left(\frac{\sum_{c,i} K_{ci}}{2} + 0.1, \sum_{c,i,k} \left(\widetilde{y}_{cikj}^{b*(m)} - W_{cik}^T \widetilde{\boldsymbol{\beta}}_j^{(m)} - \widetilde{\lambda}_j^{*(m)} U_{cik}^{*(m)} - \widetilde{\xi}_j^{(m)} b_{cij}^{*(m)} \right)^2 + 0.1 \right).$$

D3.

$$\widetilde{\lambda}_j^{*(m)} \sim \mathrm{N}\left(\widehat{\mu}_{\widetilde{\lambda}}, \widehat{\Omega}_{\widetilde{\lambda}_j} \right),$$

where

$$\hat{\mu}_{\widetilde{\lambda}} = \sum_{c,i,k} \left[\left(\widetilde{y}_{cikj}^{b*(m)} - W_{cik}^T \widetilde{\boldsymbol{\beta}}_j^{(m-1)} - \widetilde{\xi}_j^{(m-1)} b_{cij}^{*(m-1)} \right) U_{cik}^{*(m-1)} \right] \left(\sum_{c,i,k} U_{cik}^{*2(m-1)} + 1 \right)^{-1},$$

and $\widehat{\Omega}_{\widetilde{\lambda}_j} = \left[\sum_{c,i,k} U_{cik}^{*2(m-1)} + 1 \right]^{-1} \gamma_j^{2(m)}$.

D4.

$$\widetilde{\beta}_j^{*(m)} \sim \mathrm{N}\left(\widehat{\mu}_{\widetilde{\beta}}, \widehat{\Omega}_{\widetilde{\boldsymbol{\beta}}_j}\right),$$

where

$$\hat{\mu}_{\widetilde{\boldsymbol{\beta}}} = \sum_{c,i,k}\Big[\Big(\widetilde{y}_{cikj}^{b*(m)} - \widetilde{\lambda}_j^{*(m)} U_{cik}^{*(m-1)} - \widetilde{\xi}_j^{(m-1)} b_{cij}^{*(m-1)}\Big) W_{cik}\Big] \left(\sum_{c,i,k} W_{cik} W_{cik}^T + \Sigma_{\boldsymbol{\beta}}^{-1}\right)^{-1},$$

and $\widehat{\Omega}_{\widetilde{\boldsymbol{\beta}}_j} = \left[\sum_{c,i,k} W_{cik} W_{cik}^T + \Sigma_{\boldsymbol{\beta}}^{-1}\right]^{-1} \gamma_j^{2(m)}$.

D5.

$$\widetilde{\xi}_j^{(m)} \sim N\left(\left(\sum_{c,i} K_{ci} b_{cij}^{*2(m-1)} + 1\right)^{-1} \sum_{c,i,k}\left[\widetilde{y}_{cikj}^{b*(m)} - W_{cik}^T \widetilde{\boldsymbol{\beta}}_j^{(m)} - \widetilde{\lambda}_j^{*(m)} U_{cik}^{*(m-1)}\right] b_{cij}^{*(m-1)}, \Omega_{\xi_j}\right),$$

where $\Omega_{\xi_j} = \left(\sum_{c,i} K_{ci} b_{cij}^{*2(m-1)} + 1\right)^{-1} \gamma_j^{2(m)}$.

D6. Set $\boldsymbol{\beta}_j^{(m)} = \widetilde{\boldsymbol{\beta}}_j^{(m)}/\gamma_j^{(m)}$, $\lambda_j^{*(m)} = \widetilde{\lambda}_j^{*(m)}/\gamma_j^{(m)}$, and $\xi_j^{(m)} = \widetilde{\xi}_j^{(m)}/\gamma_j^{(m)}$.

D7. For each $\{c, i\}$

$$b_{cij}^{*(m)} \sim N\left(\Omega_{b_{cij}}\left[\sum_{t=1}^{K_{ci}} \xi_j^{(m)}(y_{cikj}^{b*(m)} - W_{cik}^T \boldsymbol{\beta}_j^{(m)} - \lambda_j^{*(m)} U_{cik}^{*(m-1)}) + \frac{\beta_{0j}^{*(m)}}{(\tau_j^{*(m)})^2}\right], \Omega_{b_{cij}}^{-1}\right),$$

where $\Omega_{b_{cij}} = \left(K_{ci}\xi_j^{2(m)} + \frac{1}{(\tau_j^{*(m)})^2}\right)^{-1}$.

D8. For each $\{c, i\}$, $U_{ci}^{*(m)} \sim MVN(\mu_{U_{ci}}, \Omega_{U_{ci}})$, where

$$\begin{aligned}
\mu_{U_{ci}} &= \Omega_{U_{ci}}\left[\sum_{j=1}^{J_1} \frac{\lambda_j^{*(m)}}{\sigma_j^{2(m)}}\left(\mathbf{y}_{cij}^c - \mathbf{W}_{ci}\beta_j^{(m)} - \xi_j^{(m)} b_{cij}^{*(m)} \mathbf{1}_{K_{ci}}\right)\right] \\
&+ \Omega_{U_{ci}}\left[\sum_{j=J_1}^{J} \lambda_j^{*(m)}\left(\mathbf{y}_{cij}^{b*} - \mathbf{W}_{ci}\beta_j^{(m)} - \xi_j^{(m)} b_{cij}^{*(m)} \mathbf{1}_{K_{ci}}\right)\right] \\
&+ \Omega_{U_{ci}} \frac{1}{\psi^2}\left[\mu^{*(m)} + X_{ci}\alpha^{*(m)} + g_c^{*(m-1)} 1_{K_{ci}} + Z_{ci} \bigotimes 1_{K_{ci}} a_c^{*(m-1)}\right]^T H_{ci}^{-1}(\rho^{(m)})
\end{aligned}$$

and $\Omega_{U_{ci}} = \left(\sum_{j=1}^{J_1} \frac{\lambda_j^{*2(m)}}{\sigma_j^{2(m)}} I_{K_{ci}} + \sum_{j=J_1+1}^{J} \lambda_j^{*2(m)} I_{K_{ci}} + \frac{1}{\psi^2} H_{ci}^{-1}(\rho^{(m)})\right)^{-1}$.

C Additional Simulation Plots

C.1 Model M1

Figure 1: *Comparison of Gelman-Rubin diagnostic plots for two loading factors,* λ_1 *and* λ_3 *for models* **M1** *and* **M2**. *The solid black line shows the evolution of of* R^2 *for SG, while the dashed red line shows the evolution PX-HC (for* **M1***) and* PX^2*-HC (for* **M2***)*

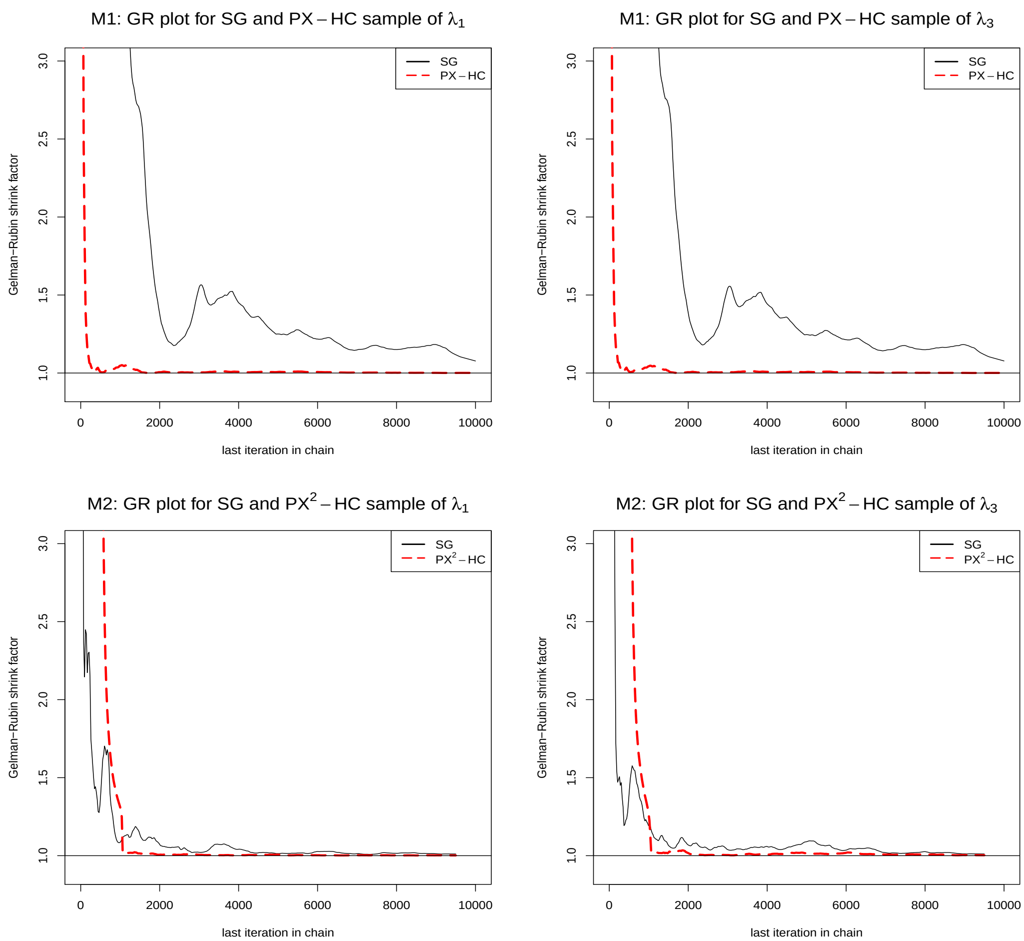


Figure 2: *Comparison of trace plots for simulations under model* **M1** *using SG and PX-HC scheme. The blue line marks the true value of the parameter, and the red line represents the posterior mean. Left side from top to bottom: trace plots for* α_1, λ_1, *and* σ_a^2 *using standard Gibbs. Right side from top to bottom: trace plots for* α_1, λ_1, *and* σ_a^2 *using* $PX-HC$.

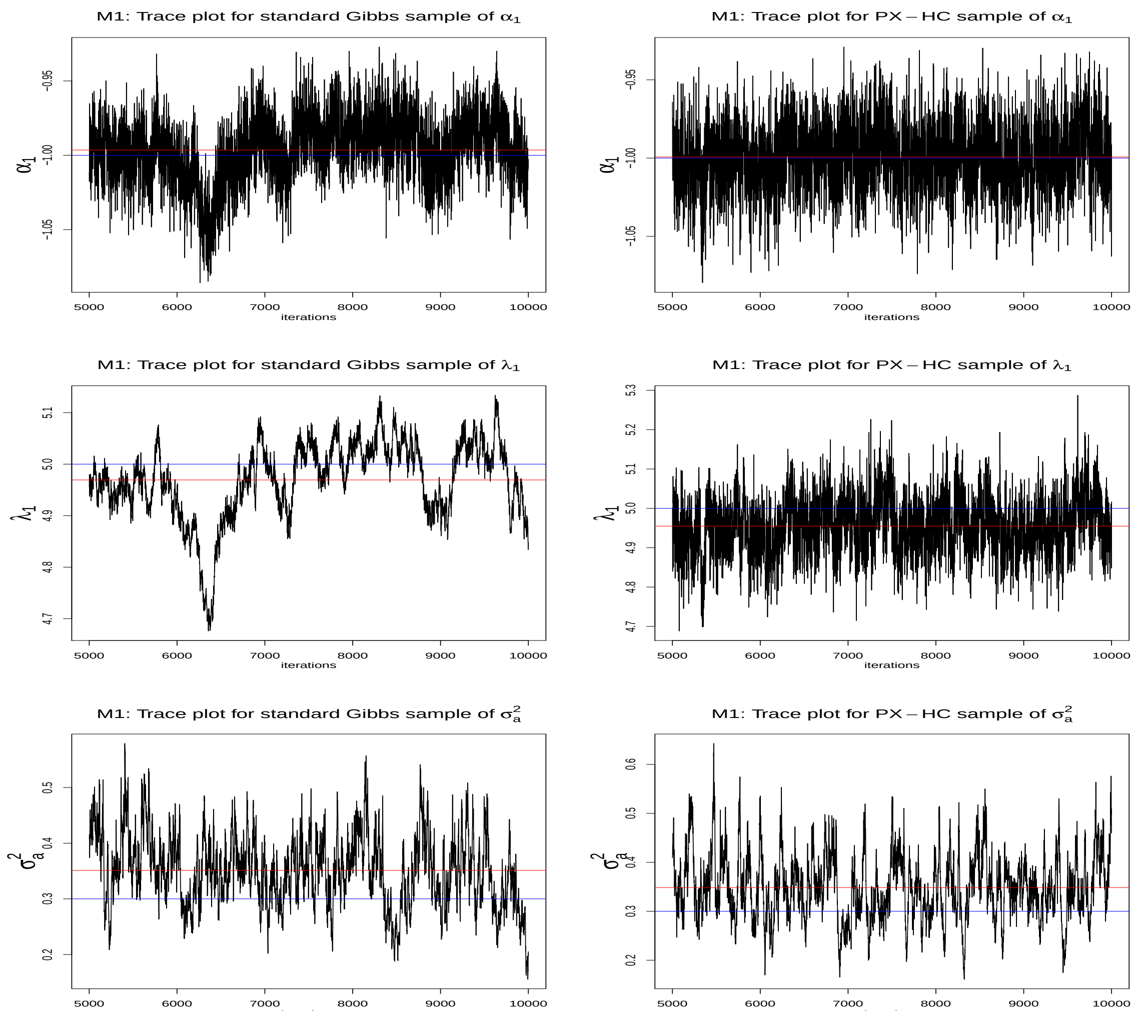


Figure 3: *Comparison of ACF plots for the three loading factors* λ_j, $j = 1, \ldots, 3$ *for model* **M1**. *Red line shows the average ACF curve for SG computed from 100 replicated curves which are shown in purple. The blue line shows the average ACF curve for PX-HC computed from 100 replicated curves which are shown in green.*

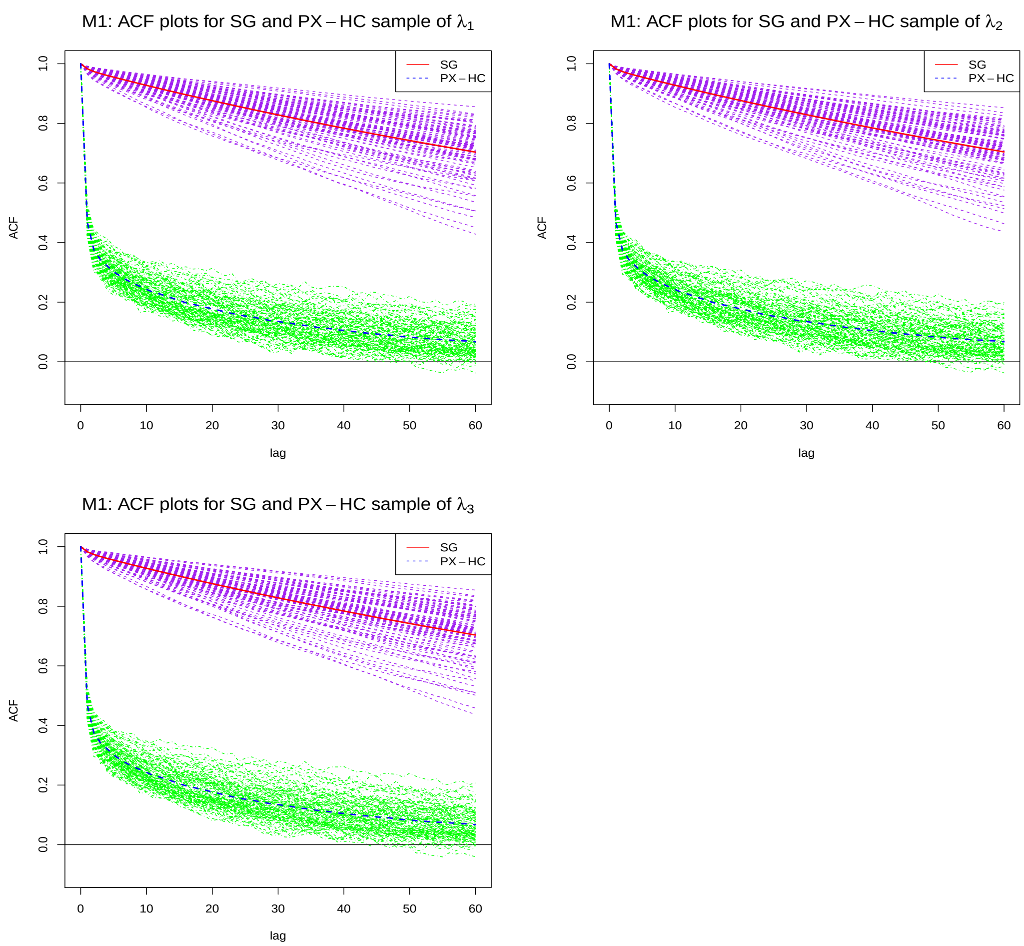
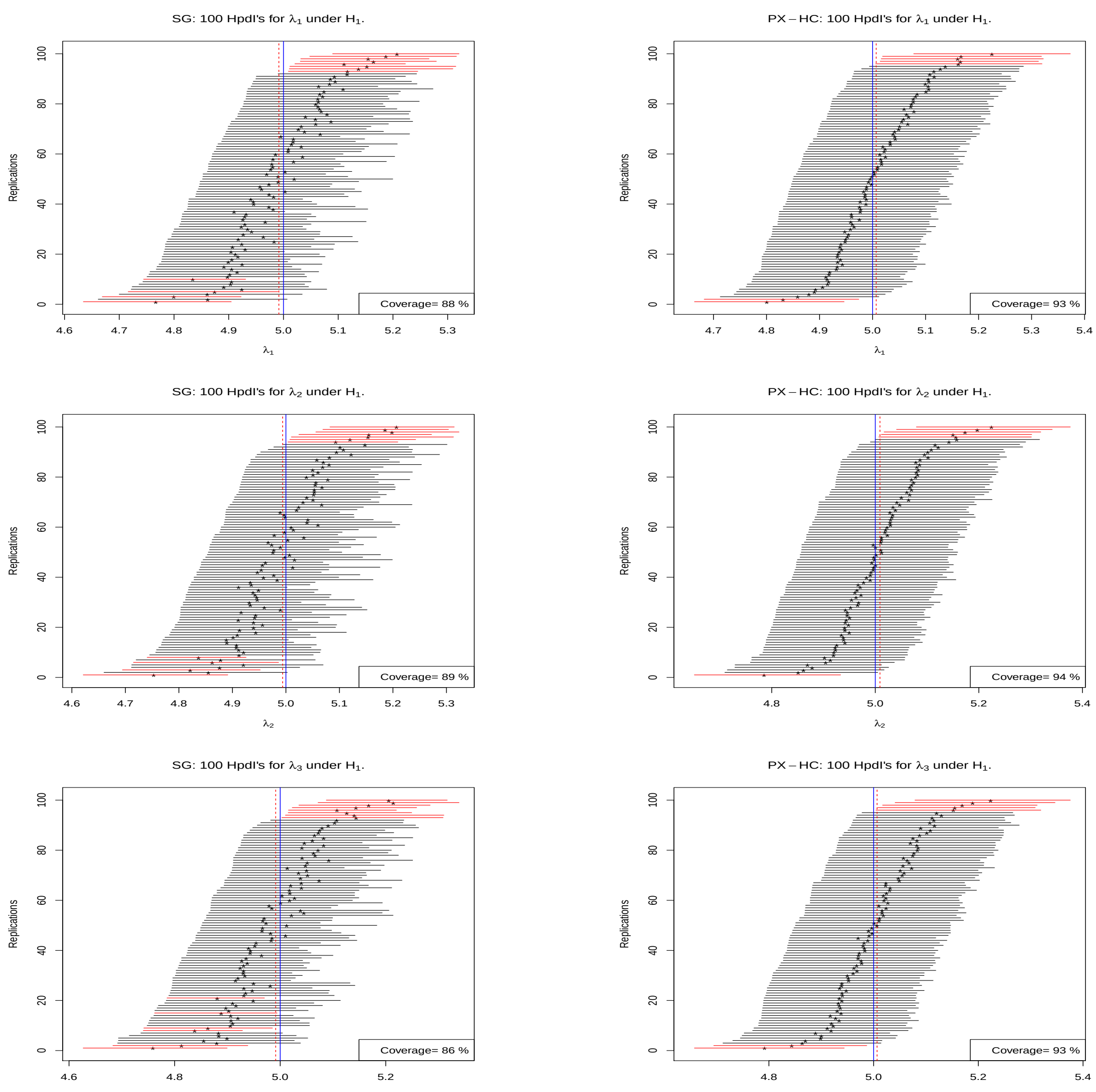


Figure 4: *Comparison of highest posterior density interval (HpdI) plots for the three loading factors λ_j, $j = 1, \ldots, 3$ for model* **M1**. *The replication number is the order of the lower bound of HpdI's. Left side: HpdI plots for λs using SG. Right side: HpdI plots for λs using PX-HC. The blue solid vertical line is the true value, which is 0, of α_2. The red dashed vertical line is the mean estimation.*



C.2 Model M2

D Additional results for the real data example.

Figure 5: *Comparison of highest posterior density interval (HpdI) plots for the three loading factors λ_j, $j = 1, \ldots, 4$ for model* **M2**. *The replication number is the order of the lower bound of HpdI's. Left side: HpdI plots for λs using SG. Right side: HpdI plots for λs using PX-HC. The blue solid vertical line is the true value, which is 0, of α_2. The red dashed vertical line is the mean estimation.*

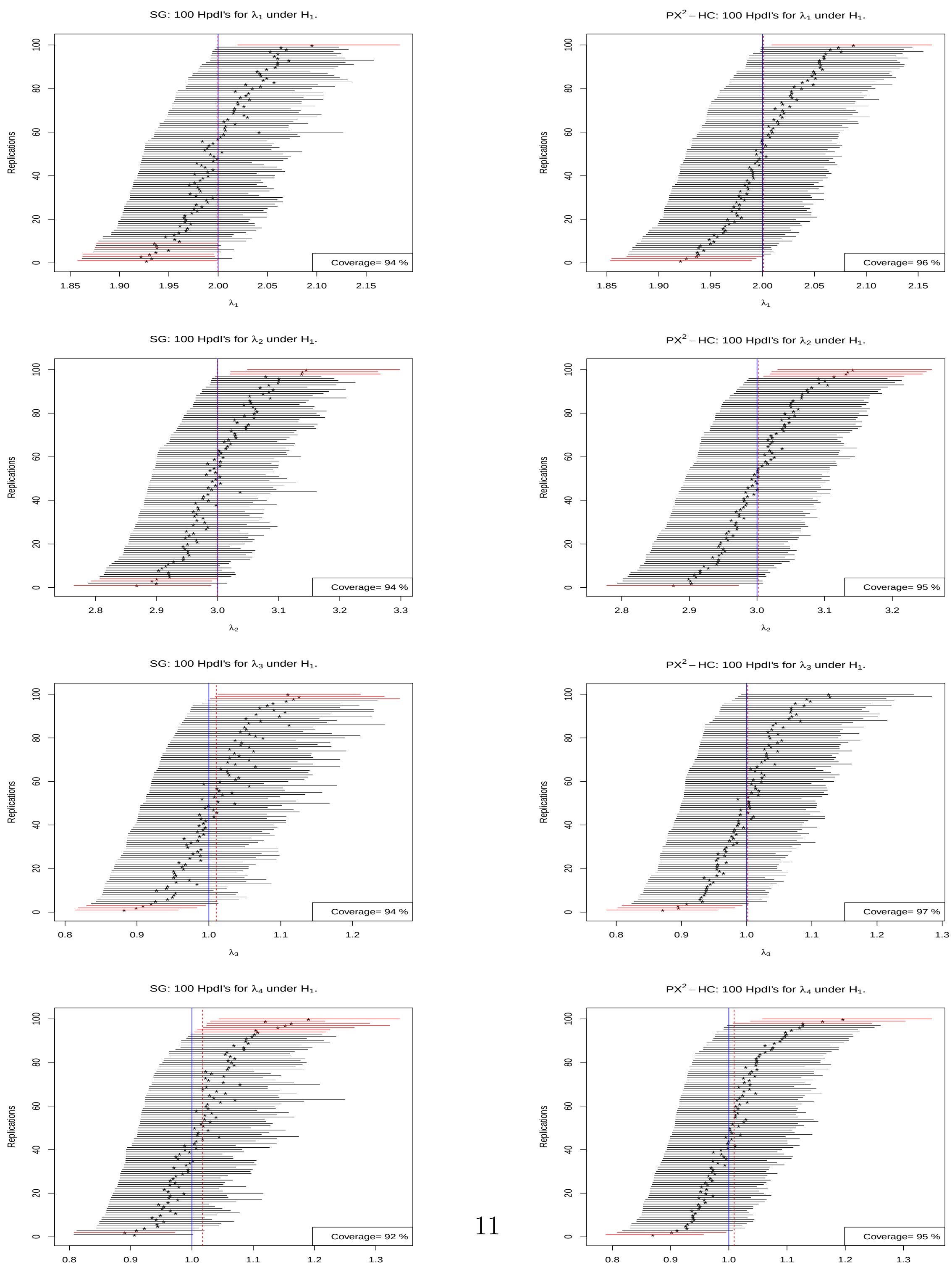


Table 1: The fitting results for the genetic study of type 1 diabetes (T1D) complications dataset using the model proposed by Roy and Lin (2000) Application results. SNP rs7842868 was previously identified to be associated with diastolic blood pressure (DBP) and SNP rs1358030 was previously identified to be associated with HbA1c. Phenotypes of interest are DBP and systolic blood pressure (SBP), two continuous outcomes, and hyperglycemia (HPG, defined as HbA1c greater or equal to 8), a binary outcome. All phenotypes are thought to be related to type 1 diabetes complication severity. The coefficient λs assess the association between the phenotypes and the latent T1D complication status, and αs evaluate the association between the latent variable and the genetic marker and the other covariates of interest. See Section 5 for more details.

		Analysis of SNP rs7842868		
	Parameter	Estimate	95% HpdI	$\widehat{logBF}$
SBP	λ_1	6.621	(6.153, 7.077)	114.85
DBP	λ_2	3.842	(3.566, 4.110)	112.98
HPG	λ_3	0.011	$(2.189 \times 10^{-7}, 2.975 \times 10^{-2})$	-1.05
rs7842868	α_1	-0.269	(-0.372, -0.164)	10.06
sex	α_2	-0.721	(-0.866, -0.584)	62.27
cohort	α_3	0.443	(0.299, 0.585)	20.15
treatment	α_4	0.128	(-0.004, 0.263)	0.366
		Analysis of SNP rs1358030		
	Parameter	Estimate	95% HpdI	$\widehat{logBF}$
SBP	λ_1	6.868	(6.439, 7.302)	128.3
DBP	λ_2	3.706	(3.491, 3.933)	120.2
HPG	λ_3	0.010	$(2.566 \times 10^{-7}, 2.740 \times 10^{-7})$	-1.034
rs1358030	α_1	- 0.039	(-0.049, 0.122)	-1.104
sex	α_2	-0.758	(-0.880, -0.623)	64.86
cohort	α_3	0.393	(0.258, 0.532)	18.17
treatment	α_4	0.088	(-0.041, 0.220)	-0.18