

# Supplementary Material for “Gaussian variational approximation with composite likelihood for crossed random effect models”

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The supplementary material contains the notation and assumptions in §S1, proofs of the main theorems for the Poisson regression model in §S2 and §S3, proofs of the main theorems for the Gamma regression model in §S4 and §S5, additional detailed simulation results in §S6, and additional details on real data analysis in §S7.

## S1 Notation and Assumptions

First, recall the Poisson regression model with crossed random effects,

$$Y_{ij} \mid \mathbf{X}_{ij}, U_i, V_j \sim \text{Poisson}(\mu_{ij}), \mu_{ij} = \exp(\mathbf{X}_{ij}^{\top} \boldsymbol{\beta}^0 + U_i + V_j), \quad (\text{S1.1})$$

$U_i \sim N(0, (\sigma_u^2)^0), V_j \sim N(0, (\sigma_v^2)^0), U_i$  and  $V_j$  are independent.

and the Gamma regression model with crossed random effects,

$$\begin{aligned}
Y_{ij} \mid \mathbf{X}_{ij}, U_i, V_j &\sim \text{Gamma}(\alpha, \mu_{ij}), \\
\mu_{ij} &= \exp(\mathbf{X}_{ij}\boldsymbol{\beta}^0 + U_i + V_j), \\
U_i &\sim N(0, (\sigma_u^2)^0), V_j \sim N(0, (\sigma_v^2)^0), U_i \text{ and } V_j \text{ are independent,}
\end{aligned} \tag{S1.2}$$

where the shape parameter  $\alpha$  is assumed known.

### S1.1 Assumptions

Our proofs rely on the following assumptions:

- (A1) The sets of variables  $\mathcal{S}_i = \{(\mathbf{X}_{ij}, Y_{ij}, U_i, V_j) : j = 1, \dots, n\}$ , for  $i = 1, \dots, m$ , are conditional independent on  $\{V_1, \dots, V_n\}$  and identically distributed, and for any given  $V_j$ , the elements  $(\mathbf{X}_{ij}, Y_{ij}, U_i), i = 1, \dots, m$ , are identically distributed as  $(\mathbf{X}, Y, U)$ .
- (A2) The sets of variables  $\mathcal{S}'_j = \{(\mathbf{X}_{ij}, Y_{ij}, U_i, V_j) : i = 1, \dots, m\}$ , for  $j = 1, \dots, n$ , are conditional independent on  $\{U_1, \dots, U_m\}$  and identically distributed, and for any given  $U_i$ , the elements  $(\mathbf{X}_{ij}, Y_{ij}, V_j), j = 1, \dots, n$ , are identically distributed as  $(\mathbf{X}, Y, V)$ .
- (A3) The quadruples  $(\mathbf{X}_{ij}, Y_{ij}, U_i, V_j)$  and  $(\mathbf{X}_{kl}, Y_{kl}, U_k, V_l)$  for  $k \neq i, l \neq j$  are mutually independent and identically distributed as  $(X, Y, U, V)$ .
- (A4) The random variables  $\mathbf{X}$ ,  $U$ , and  $V$  are mutually independent.

- (A5) The true values  $\beta^0$ ,  $(\sigma_u^2)^0$ , and  $(\sigma_v^2)^0$  of  $\beta$ ,  $\sigma_u^2$ , and  $\sigma_v^2$ , respectively, lie in  $\mathbb{R}^p$ ,  $(0, \infty)$ , and  $(0, \infty)$ ; when choosing  $(\hat{\beta}, \hat{\sigma}_u^2, \hat{\sigma}_v^2, \hat{\mu}_u, \hat{\lambda}_u, \hat{\mu}_v, \hat{\lambda}_v)$  we search in the rectangular region  $[-C_1, C_1]^p \times [C_1^{-1}, C_1] \times [C_1^{-1}, C_1] \times [-C_2, C_2]^m \times [-C_1, C_1]^m \times [-C_2, C_2]^n \times [-C_1, C_1]^n$ , where  $C_1$  is a constant satisfying  $C_1 > \max\{|\beta_0^0|, \dots, |\beta_p^0|, (\sigma_u^2)^0, 1/(\sigma_u^2)^0, (\sigma_v^2)^0, 1/(\sigma_v^2)^0\}$  and  $C_2$  is a sufficiently large but finite positive constant.
- (A6) The moment generating function of  $\mathbf{X} = (X_1, \dots, X_p)^\top$ ,  $\phi(t) = E\{\exp(\mathbf{X}^\top t)\}$  is well defined in  $\mathbb{R}^p$ .
- (A7) The functions

$$\phi_1(t) = E_{\mathbf{X}}\{\mathbf{X} \exp(\mathbf{X}^\top t)\},$$

$$\phi_2(t) = E_{\mathbf{X}}\{\mathbf{X} \mathbf{X}^\top \exp(\mathbf{X}^\top t)\},$$

are well defined for all vector  $t$ . For simplicity, we denote  $\phi(\cdot) = \phi_0(\cdot)$ ;

- (A8) In some neighborhood of  $\beta_{-1}^0 = (\beta_2^0, \dots, \beta_p^0)^\top$ ,  $(d^2/d\beta_i^2) \log\{\phi(\beta_i)\}$  does not vanish,  $i = 1, \dots, p$ ;
- (A9) The mapping that takes  $\beta$  to  $\phi_1(\beta)/\phi(\beta)$  is invertible.

The assumptions (A6), (A8) and (A9) were used explicitly by Hall et al. (2011), whilst (A1)-(A5) are the extensions of (A1)-(A3) and (A11) of Hall et al. (2011). Assumption (A7) was used to make the results representation concise by Ormerod and Wand (2012).

## S1.2 Notation

Denote  $\Psi^{rc} = (\beta_1^r, \beta_1^c, \boldsymbol{\beta}_{-1}^T, \sigma_u^2, \sigma_v^2)^T$ ,  $\boldsymbol{\xi} = (\mu_{u_1}, \dots, \mu_{u_m}, \mu_{v_1}, \dots, \mu_{v_n}, \lambda_{u_1}, \dots, \lambda_{u_m}, \lambda_{v_1}, \dots, \lambda_{v_n})^T$ ;  $\widehat{\underline{\beta}}_1^r$  the variational composite likelihood estimate (VCLE) of  $\beta_1^{r0} = \beta_1^0 + \sigma_v^2/2$ ;  $\widehat{\underline{\beta}}_1^c$  the VCLE of  $\beta_1^{c0} = \beta_1^0 + \sigma_u^2/2$ ;  $\widehat{\underline{\beta}}_1$  the VCLE of intercept  $\beta_0^0$ ;  $\widehat{\underline{\beta}}_i$  the VCLE of the covariate coefficient  $\beta_i^0, i = 2, \dots, p$ ;  $\widehat{\underline{\sigma}}_u^2$  the VCLE of variance of random effect  $U, (\sigma_u^2)^0$ ;  $\widehat{\underline{\sigma}}_v^2$  the VCLE of variance of random effect  $V, (\sigma_v^2)^0$ ;  $\widehat{\underline{\mu}}_{u_i}, \widehat{\underline{\lambda}}_{u_i}$  the VCLEs of parameters of the  $i$ -th variational distribution  $N(\mu_{u_i}, \lambda_{u_i}), i = 1, \dots, m$ ;  $\widehat{\underline{\mu}}_{v_j}, \widehat{\underline{\lambda}}_{v_j}$  the VCLEs of parameters of the  $j$ -th variational distribution  $N(\mu_{v_j}, \lambda_{v_j}), j = 1, \dots, n$ .

## S2 Proof of Theorem 1 for Poisson regression model

The proof for the consistency and rates of convergence for the estimators

$\widehat{\underline{\beta}}_1, \widehat{\underline{\beta}}_{-1}, \widehat{\underline{\sigma}}_u^2$ , and  $\widehat{\underline{\sigma}}_v^2$  involves two main steps:

Step1. Establish the consistency of estimators  $\beta_1^0, \boldsymbol{\beta}_{-1}^0, (\sigma_u^2)^0$ , and  $(\sigma_v^2)^0$  in §S2.1;

Step2. Extend the consistency results to a rate of convergence by controlling the remainder terms in §S2.2.

### S2.1 Consistency

The variational lower bound of the CL for the Poisson regression model with crossed random effects is

$$\begin{aligned}
& \underline{\mathcal{C}}\ell(\boldsymbol{\Psi}^{rc}, \boldsymbol{\xi}) \\
&= \sum_{i=1}^m \sum_{j=1}^n \{Y_{ij}(\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i}) - \exp(\mathbf{X}_{ij} \boldsymbol{\beta}^r + \mu_{u_i} + \lambda_{u_i}/2)\} \\
&\quad - \frac{m}{2} \log(\sigma_u^2) - \frac{1}{2\sigma_u^2} \sum_{i=1}^m (\mu_{u_i}^2 + \lambda_{u_i}) + \frac{1}{2} \log \lambda_{u_i} \\
&\quad + \sum_{j=1}^n \sum_{i=1}^m \{Y_{ij}(\mathbf{X}_{ij}^T \boldsymbol{\beta}^c + \mu_{v_j}) - \exp(\mathbf{X}_{ij} \boldsymbol{\beta}^c + \mu_{v_j} + \lambda_{v_j}/2)\} \\
&\quad - \frac{n}{2} \log(\sigma_v^2) - \frac{1}{2\sigma_v^2} \sum_{j=1}^n (\mu_{v_j}^2 + \lambda_{v_j}) + \frac{1}{2} \log \lambda_{v_j}.
\end{aligned}$$

To derive the consistency of the estimates, we take derivatives of  $\underline{\mathcal{C}}\ell(\boldsymbol{\Psi}^{rc}, \boldsymbol{\xi})$  with respect to the parameters.

$$\frac{\partial \underline{\mathcal{C}}\ell(\boldsymbol{\Psi}^{rc}, \boldsymbol{\xi})}{\partial \beta_1^r} = \sum_{i=1}^m \sum_{j=1}^n \left( Y_{ij} - e^{\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i} + \lambda_{u_i}/2} \right), \quad (\text{S2.3})$$

$$\frac{\partial \underline{\mathcal{C}}\ell(\boldsymbol{\Psi}^{rc}, \boldsymbol{\xi})}{\partial \beta_1^c} = \sum_{i=1}^m \sum_{j=1}^n \left( Y_{ij} - e^{\mathbf{X}_{ij}^T \boldsymbol{\beta}^c + \mu_{v_j} + \lambda_{v_j}/2} \right), \quad (\text{S2.4})$$

$$\begin{aligned}
\frac{\partial \underline{\mathcal{C}}\ell(\boldsymbol{\Psi}^{rc}, \boldsymbol{\xi})}{\partial \beta_{-1}} &= \sum_{i=1}^m \sum_{j=1}^n \left( Y_{ij} - e^{\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i} + \lambda_{u_i}/2} \right) \mathbf{X}_{ij, -1} \\
&\quad + \sum_{i=1}^m \sum_{j=1}^n \left( Y_{ij} - e^{\mathbf{X}_{ij}^T \boldsymbol{\beta}^c + \mu_{v_j} + \lambda_{v_j}/2} \right) \mathbf{X}_{ij, -1},
\end{aligned} \quad (\text{S2.5})$$

$$\frac{\partial \underline{c\ell}(\Psi^{rc}, \xi)}{\partial \sigma_u^2} = -\frac{m}{2\sigma_u^2} + \frac{1}{2\sigma_u^4} \sum_{i=1}^m (\mu_{u_i}^2 + \lambda_{u_i}), \quad (\text{S2.6})$$

$$\frac{\partial \underline{c\ell}(\Psi^{rc}, \xi)}{\partial \sigma_v^2} = -\frac{n}{2\sigma_v^2} + \frac{1}{2\sigma_v^4} \sum_{j=1}^n (\mu_{v_j}^2 + \lambda_{v_j}), \quad (\text{S2.7})$$

for each  $\mu_{u_i}$  and  $\lambda_{u_i}$ ,

$$\frac{\partial \underline{c\ell}(\Psi^{rc}, \xi)}{\partial \mu_{u_i}} = \sum_{j=1}^n \left( Y_{ij} - e^{\mathbf{x}_{ij}^T \beta^r + \mu_{u_i} + \lambda_{u_i}/2} \right) - \frac{\mu_{u_i}}{\sigma_u^2}, \quad (\text{S2.8})$$

$$\frac{\partial \underline{c\ell}(\Psi^{rc}, \xi)}{\partial \lambda_{u_i}} = -\frac{1}{2} \sum_{j=1}^n e^{\mathbf{x}_{ij}^T \beta^r + \mu_{u_i} + \lambda_{u_i}/2} - \frac{1}{2\sigma_u^2} + \frac{1}{2\lambda_{u_i}}, \quad (\text{S2.9})$$

for each  $\mu_{v_j}$  and  $\lambda_{v_j}$ ,

$$\frac{\partial \underline{c\ell}(\Psi^{rc}, \xi)}{\partial \mu_{v_j}} = \sum_{i=1}^m \left( Y_{ij} - e^{\mathbf{x}_{ij}^T \beta^r + \mu_{v_j} + \lambda_{v_j}/2} \right) - \frac{\mu_{v_j}}{\sigma_v^2}, \quad (\text{S2.10})$$

$$\frac{\partial \underline{c\ell}(\Psi^{rc}, \xi)}{\partial \lambda_{v_j}} = -\frac{1}{2} \sum_{i=1}^m e^{\mathbf{x}_{ij}^T \beta^r + \mu_{v_j} + \lambda_{v_j}/2} - \frac{1}{2\sigma_v^2} + \frac{1}{2\lambda_{v_j}}. \quad (\text{S2.11})$$

Setting equations (S2.6) and (S2.7) to zeros and solving we obtain

$$\hat{\sigma}_u^2 = \frac{1}{m} \sum_{i=1}^m (\hat{\mu}_{u_i}^2 + \hat{\lambda}_{u_i}), \quad (\text{S2.12})$$

$$\hat{\sigma}_v^2 = \frac{1}{n} \sum_{j=1}^n (\hat{\mu}_{v_j}^2 + \hat{\lambda}_{v_j}). \quad (\text{S2.13})$$

Setting (S2.3), (S2.4), (S2.8), and (S2.10) to zeros we have

$$\sum_{i=1}^m \sum_{j=1}^n \left( Y_{ij} - e^{\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i} + \lambda_{u_i}/2} \right) = 0, \quad (\text{S2.14})$$

$$\sum_{i=1}^m \sum_{j=1}^n \left( Y_{ij} - e^{\mathbf{X}_{ij}^T \boldsymbol{\beta}^c + \mu_{v_j} + \lambda_{v_j}/2} \right) = 0, \quad (\text{S2.15})$$

$$\sum_{j=1}^n \left( Y_{ij} - e^{\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i} + \lambda_{u_i}/2} \right) - \frac{\mu_{u_i}}{\sigma_u^2} = 0, i = 1, \dots, m, \quad (\text{S2.16})$$

$$\sum_{i=1}^m \left( Y_{ij} - e^{\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i} + \lambda_{u_i}/2} \right) - \frac{\mu_{v_j}}{\sigma_v^2} = 0, j = 1, \dots, n. \quad (\text{S2.17})$$

By (S2.16), we have

$$\sum_{i=1}^m \sum_{j=1}^n \left( Y_{ij} - e^{\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i} + \lambda_{u_i}/2} \right) - \sum_{i=1}^m \frac{\mu_{u_i}}{\sigma_u^2} = 0. \quad (\text{S2.18})$$

Combining (S2.14) and (S2.18) we have

$$\sum_{i=1}^m \hat{\underline{\mu}}_{u_i} = 0. \quad (\text{S2.19})$$

By (S2.17), we have

$$\sum_{i=1}^m \sum_{j=1}^n \left( Y_{ij} - e^{\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i} + \lambda_{u_i}/2} \right) - \sum_{i=1}^m \frac{\mu_{v_j}}{\sigma_v^2} = 0. \quad (\text{S2.20})$$

Combining (S2.15) and (S2.20) we have

$$\sum_{j=1}^n \hat{\underline{\mu}}_{v_j} = 0. \quad (\text{S2.21})$$

Setting equations (S2.9) and (S2.11) to zeros we have  $\hat{\underline{\lambda}}_{u_i}$  and  $\hat{\underline{\lambda}}_{v_j}$  satisfy

$$\hat{\underline{\lambda}}_{u_i} = \left\{ \sigma_u^{-2} + \sum_{j=1}^n \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \hat{\underline{\mu}}_{u_i} + \hat{\underline{\lambda}}_{u_i}/2) \right\}^{-1}, \quad (\text{S2.22})$$

and

$$\hat{\underline{\lambda}}_{v_j} = \left\{ \sigma_v^{-2} + \sum_{i=1}^m \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^c + \hat{\underline{\mu}}_{v_j} + \hat{\underline{\lambda}}_{v_j}/2) \right\}^{-1},$$

from which it is obvious that  $0 < \hat{\underline{\lambda}}_{u_i} < \sigma_u^2$  and  $0 < \hat{\underline{\lambda}}_{v_j} < \sigma_v^2$ .

Since  $\mathbf{X}$  has a finite moment generating function  $\phi$  on  $\mathbb{R}^p$ ,  $\boldsymbol{\beta}_{-1} \in [-C_1, C_1]^{p-1}$ ,  $\exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1})$  is continuous in  $[-C_1, C_1]^{p-1}$  with probability one, and  $\exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) \leq \exp(C_1 \|\mathbf{X}_{ij}\|)$ , by the uniform law of large numbers in Jennrich (1969), we have

$$\sup_{\boldsymbol{\theta} \in \Theta} \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) \right| \rightarrow 0,$$

in probability, i.e., for all  $\epsilon > 0$ , we have

$$\lim_{n \rightarrow \infty} P \left\{ \sup_{\boldsymbol{\beta}_{-1} \in [-C_1, C_1]^{p-1}} \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) \right| > \epsilon \right\} = 0.$$

For the compact interval  $[-C_1, C_1]^{p-1}$ , we can find a finite sub-cover such that  $[-C_1, C_1]^{p-1}$  is covered by  $\cup_{k=1}^K B(\boldsymbol{\beta}_{-1,k}, \delta)$ , and

$$\begin{aligned} & P \left\{ \sup_{\boldsymbol{\beta}_{-1} \in [-C_1, C_1]^{p-1}} \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) \right| > \epsilon \right\} \quad (\text{S2.23}) \\ &= P \left\{ \sup_{\boldsymbol{\beta}_{-1} \in [-C_1, C_1]^{p-1}} \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}) - \phi(\boldsymbol{\beta}_{-1}) \right|^q > \epsilon^q \right\} \\ &= P \left\{ \max_{k \in [1, \dots, K]} \sup_{\boldsymbol{\beta}_{-1} \in B(\boldsymbol{\beta}_{-1,k}, \delta)} \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) \right|^q > \epsilon^q \right\}. \end{aligned}$$

In each interval  $B(\boldsymbol{\beta}_{-1,k}, \delta)$ , we can find a sub-sequence  $\mathcal{S}_n^k = \{\boldsymbol{\beta}_{-1,k,l}, l =$

$1, \dots, C_0 n^{C'}\}$ ,  $C_0$  and  $C'$  are positive constants, such that

$$\begin{aligned} -\epsilon^q &< \sup_{\boldsymbol{\beta}_{-1} \in B(\boldsymbol{\beta}_{-1,k}, \delta)} \left| \frac{1}{n} \sum_{i=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) \right|^q \\ &\quad - \sup_{\boldsymbol{\beta}_{-1} \in \mathcal{S}_n^k} \left| \frac{1}{n} \sum_{i=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) \right|^q < \epsilon^q \end{aligned}$$

Then by (S2.23), we have

$$\begin{aligned} &P \left\{ \sup_{\boldsymbol{\beta}_{-1} \in [-C_1, C_1]^{p-1}} \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) \right| > \epsilon \right\} \\ &\leq P \left\{ \max_{k \in \{1, \dots, K\}} \sup_{\boldsymbol{\beta}_{-1} \in \mathcal{S}_n^k} \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) \right|^q > 2\epsilon^q \right\} \\ &\leq P \left[ \bigcup_{k=1}^K \bigcup_{l=1}^{C_0 n^{C'}} \left\{ \omega : \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) \right|^q > 2\epsilon^q \right\} \right] \\ &\leq \sum_{k=1}^K \sum_{l=1}^{C_0 n^{C'}} P \left\{ \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) \right|^q > 2\epsilon^q \right\} \\ &\leq 0.5 K C_0 n^{C'} \epsilon^{-q} E \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) \right|^q. \end{aligned}$$

Since for any  $\boldsymbol{\beta}_{-1}$ ,

$$\frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) = O_p(n^{-1/2}),$$

taking  $\epsilon = n^{-\rho}$ ,  $\rho \in (0, 1/2)$ , and by

$$E \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) \right|^q = O(n^{-q/2}),$$

we have

$$\begin{aligned} &P \left\{ \sup_{\boldsymbol{\beta}_{-1} \in [-C_1, C_1]^{p-1}} \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) - \phi(\boldsymbol{\beta}_{-1}) \right| > \epsilon \right\} \\ &\leq 0.5 K C_0 n^{1+\rho C'} O(n^{-q/2}) = O(n^{-C_2}), \end{aligned}$$

where  $q$  satisfies  $C_2 = q/2 - (1 + q\rho)C' > 0$ .

Therefore, under assumption  $m = O(n^C)$ , we have following properties

$$\begin{aligned}
& P \left\{ \max_{1 \leq i \leq m} \sup_{\beta_{-1}: \|\beta_{-1}\| \leq C_1} \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \beta_{-1}) - \phi(\beta_{-1}) \right| > n^{-\rho} \right\} \\
& \leq \sum_{i=1}^{c_1 n^C} P \left\{ \sup_{\beta_{-1}: \|\beta_{-1}\| \leq C_1} \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \beta_{-1}) - \phi(\beta_{-1}) \right| > n^{-\rho} \right\} \\
& = O(n^{-C_2}), \tag{S2.24}
\end{aligned}$$

where  $C_2 = q/2 - C - (1 + q\rho)C' > 0$ . Since we always can choose a large  $q$  such that  $C_2 > 0$ , without loss of generality, we will assume  $C_2 > 0$  changes with lines. By the similar proof process of (S2.24), we derive that

$$\begin{aligned}
& P \left\{ \max_{1 \leq j \leq n} \sup_{\beta_{-1}: \|\beta_{-1}\| \leq C_1} \left| \frac{1}{m} \sum_{i=1}^m \exp(\mathbf{X}_{ij,-1}^T \beta_{-1}) - \phi(\beta_{-1}) \right| > m^{-\rho} \right\} \\
& = O(m^{-C_2}), \tag{S2.25}
\end{aligned}$$

The following two properties follow the similar proof process of (S2.24)

and (S2.25), respectively,

$$\begin{aligned}
& P \left\{ \max_{1 \leq i \leq m} \sup_{\beta_{-1}: \|\beta_{-1}\| \leq C_1} \left\| \frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij,-1}^T \exp(\mathbf{X}_{ij,-1}^T \beta_{-1}) - \phi_1(\beta_{-1}) \right\| > n^{-\rho} \right\} \\
& = O(n^{-C_2}). \tag{S2.26}
\end{aligned}$$

and

$$\begin{aligned}
& P \left\{ \max_{1 \leq j \leq n} \sup_{\beta_{-1}: \|\beta_{-1}\| \leq C_1} \left\| \frac{1}{m} \sum_{i=1}^m \mathbf{X}_{ij,-1}^T \exp(\mathbf{X}_{ij,-1}^T \beta_{-1}) - \phi_1(\beta_{-1}) \right\| > m^{-\rho} \right\} \\
& = O(m^{-C_2}). \tag{S2.27}
\end{aligned}$$

Since  $\mathbf{X}_{ij,-1}$ ,  $U_i$ , and  $V_j$  are mutually independent,  $E\{\exp(\mathbf{X}_{ij,-1}^\top \boldsymbol{\beta}_{-1} + V_j)\} = \phi(\boldsymbol{\beta}_{-1}) \exp\{(\sigma_v^2)^0/2\}$  and  $E\{\exp(\mathbf{X}_{ij,-1}^\top \boldsymbol{\beta}_{-1} + U_i)\} = \phi(\boldsymbol{\beta}_{-1}) \exp\{(\sigma_u^2)^0/2\}$ .

Then we can derive analogously that

$$P\left\{\max_{1 \leq i \leq n} \sup_{\boldsymbol{\beta}_{-1}: \|\boldsymbol{\beta}_{-1}\| \leq C_1} \left| \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^\top \boldsymbol{\beta}_{-1} + V_j) - \phi(\boldsymbol{\beta}_{-1}) \exp(\sigma_v^2/2) \right| > n^{-\rho} \right\} = O(n^{-C_2}). \quad (\text{S2.28})$$

and

$$P\left\{\max_{1 \leq j \leq m} \sup_{\boldsymbol{\beta}_{-1}: \|\boldsymbol{\beta}_{-1}\| \leq C_1} \left| \frac{1}{m} \sum_{i=1}^m \exp(\mathbf{X}_{ij,-1}^\top \boldsymbol{\beta}_{-1} + U_i) - \phi(\boldsymbol{\beta}_{-1}) \exp(\sigma_u^2/2) \right| > m^{-\rho} \right\} = O(m^{-C_2}). \quad (\text{S2.29})$$

For the independent normal random variables  $U_1, \dots, U_m$ , they have the following property,

$$P\left\{\max_{1 \leq i \leq m} U_i \geq \sigma_u(2D \log m)^{1/2}\right\} \leq m^{1-D},$$

by assumption  $m = O(n^C)$ , there exists  $C' > 0$  such that

$$P\left[\max_{1 \leq i \leq m} \exp(U_i) \geq \exp\{C'(\log n)^{1/2}\}\right] \rightarrow 0. \quad (\text{S2.30})$$

Similarly, by the assumption  $n = O(m^{C^*})$ , there exists  $C''$  such that

$$P\left[\max_{1 \leq j \leq n} \exp(V_j) \geq \exp\{C''(\log m)^{1/2}\}\right] \rightarrow 0. \quad (\text{S2.31})$$

Since for each  $1 \leq i \leq m$ , conditional on  $\mathbf{X}_{ij}, U_i$ , and  $V_j$ ,  $Y_{ij}$  follows independent Poisson with mean  $\exp(\mathbf{X}_{ij}^\top \boldsymbol{\beta} + U_i + V_j)$ ,  $1 \leq j \leq n$ . It therefore

can be proved using Markov's inequality that there exists a positive constant  $C'_2$  and for  $\rho \in (0, 1/2)$ ,

$$\max_{1 \leq i \leq m} P \left[ \left| \frac{1}{n} \sum_{j=1}^n \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + U_i + V_j)\} \right| > n^{-\rho} \right] = O(n^{-C'_2}).$$

Hence, by the assumption  $m = O(n^C)$ ,

$$\begin{aligned} & P \left[ \max_{1 \leq i \leq m} \left| \frac{1}{n} \sum_{j=1}^n \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + U_i + V_j)\} \right| > n^{-\rho} \right] \\ &= P \left( \bigcup_{i=1}^m \left[ \omega : \left| \frac{1}{n} \sum_{j=1}^n \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + U_i + V_j)\} \right| > n^{-\rho} \right] \right) \\ &\leq \sum_{i=1}^{C_1 n^C} P \left( \left[ \omega : \left| \frac{1}{n} \sum_{j=1}^n \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + U_i + V_j)\} \right| > n^{-\rho} \right] \right) \\ &\leq O(n^{C-C'_2}) = O(n^{-C_2}), \end{aligned} \tag{S2.32}$$

where  $C_1$  is a positive constant. Combining (S2.28), (S2.30), and (S2.32), we can choose  $C'_2$  such that  $C_2 = C'_2 - C > 0$  and for any  $\rho \in (0, 1/2)$ , we have

$$\begin{aligned} & P \left\{ \max_{1 \leq i \leq m} \left| \frac{1}{n} \sum_{j=1}^n Y_{ij} - \exp \left\{ \beta_1^0 + \frac{1}{2}(\sigma_v^2)^0 + U_i \right\} \phi(\boldsymbol{\beta}_{-1}^0) \right| > n^{-\rho} \right\} \\ &= O(n^{-C_2}), \end{aligned} \tag{S2.33}$$

which implies

$$\begin{aligned} & P \left\{ \left| \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n Y_{ij} - \exp \left\{ \beta_1^0 + \frac{1}{2}(\sigma_u^2)^0 + \frac{1}{2}(\sigma_v^2)^0 \right\} \phi(\boldsymbol{\beta}_{-1}^0) \right| > n^{-\rho} \right\} \\ &= O(n^{-C_2}). \end{aligned}$$

Combining results (S2.29) and (S2.31), similar to the derivation of (S2.33),

we have

$$\begin{aligned}
 & P \left\{ \max_{1 \leq j \leq n} \left| \frac{1}{m} \sum_{i=1}^m Y_{ij} - \exp \left\{ \beta_1^0 + \frac{1}{2}(\sigma_u^2)^0 + V_j \right\} \phi(\boldsymbol{\beta}_{-1}^0) \right| > m^{-\rho} \right\} \\
 &= O(m^{-C_2}), \tag{S2.34}
 \end{aligned}$$

which implies

$$\begin{aligned}
 & P \left\{ \left| \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n Y_{ij} - \exp \left\{ \beta_1^0 + \frac{1}{2}(\sigma_u^2)^0 + \frac{1}{2}(\sigma_v^2)^0 \right\} \phi(\boldsymbol{\beta}_{-1}^0) \right| > m^{-\rho} \right\} \\
 &= O(m^{-C_2}).
 \end{aligned}$$

By the similar derivation of (S2.33) again, we can also obtain that

$$\begin{aligned}
 & P \left\{ \max_{1 \leq i \leq m} \left\| \frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij} Y_{ij} \right. \right. \\
 & \quad \left. \left. - \exp \left\{ \beta_1^0 + \frac{1}{2}(\sigma_u^2)^0 + \frac{1}{2}(\sigma_v^2)^0 \right\} \phi_1(\boldsymbol{\beta}_{-1}^0) \right\| > n^{-\rho} \right\} = O(n^{-C_2}),
 \end{aligned}$$

which implies

$$\begin{aligned}
 & P \left\{ \left\| \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij} Y_{ij} \right. \right. \tag{S2.35} \\
 & \quad \left. \left. - \exp \left\{ \beta_1^0 + \frac{1}{2}(\sigma_u^2)^0 + \frac{1}{2}(\sigma_v^2)^0 \right\} \phi_1(\boldsymbol{\beta}_{-1}^0) \right\| > n^{-\rho} \right\} = O(n^{-C_2}),
 \end{aligned}$$

and

$$\begin{aligned}
 & P \left\{ \max_{1 \leq i \leq n} \left\| \frac{1}{m} \sum_{j=1}^m \mathbf{X}_{ij} Y_{ij} \right. \right. \\
 & \quad \left. \left. - \exp \left\{ \beta_1^0 + \frac{1}{2}(\sigma_u^2)^0 + \frac{1}{2}(\sigma_v^2)^0 \right\} \phi_1(\boldsymbol{\beta}_{-1}^0) \right\| > m^{-\rho} \right\} = O(m^{-C_2}),
 \end{aligned}$$

which implies

$$P\left\{\left\|\frac{1}{mn}\sum_{i=1}^m\sum_{j=1}^n\mathbf{X}_{ij}Y_{ij}\right.\right. \quad (S2.36)$$

$$\left.\left.-\exp\left\{\beta_1^0+\frac{1}{2}(\sigma_u^2)^0+\frac{1}{2}(\sigma_v^2)^0\right\}\phi_1(\boldsymbol{\beta}_{-1}^0)\right\|>m^{-\rho}\right\}=O(m^{-C_2}).$$

In the following content, we denote  $\beta_1^{r0} = \beta_1^0 + (\sigma_u^2)^0/2$  and  $\beta_1^{c0} = \beta_1^0 + (\sigma_v^2)^0/2$ .

Equating equations (S2.8), (S2.9), (S2.10), and (S2.11) to zero and solving, the estimates  $\hat{\underline{\mu}}_{u_i}, \hat{\underline{\lambda}}_{u_i}, \hat{\underline{\mu}}_{v_j}$ , and  $\hat{\underline{\lambda}}_{v_j}$  can be obtained. And then plugging them into the equations, we have

$$\frac{1}{n}\sum_{j=1}^n Y_{ij} = \exp(\beta_1^r + \hat{\underline{\mu}}_{u_i} + \hat{\underline{\lambda}}_{u_i}/2) \frac{1}{n}\sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) + \frac{\hat{\underline{\mu}}_{u_i}}{n\sigma_u^2}, \quad (S2.37)$$

$$\frac{1}{n\hat{\underline{\lambda}}_{u_i}} = \exp(\beta_1^r + \hat{\underline{\mu}}_{u_i} + \hat{\underline{\lambda}}_{u_i}/2) \frac{1}{n}\sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) + \frac{1}{n\sigma_u^2} \quad (S2.38)$$

and

$$\frac{1}{m}\sum_{i=1}^m Y_{ij} = \exp(\beta_1^c + \hat{\underline{\mu}}_{v_j} + \hat{\underline{\lambda}}_{v_j}/2) \frac{1}{m}\sum_{i=1}^m \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) + \frac{\hat{\underline{\mu}}_{v_j}}{\sigma_v^2}, \quad (S2.39)$$

$$\frac{1}{m\hat{\underline{\lambda}}_{v_j}} = \exp(\beta_1^c + \hat{\underline{\mu}}_{v_j} + \hat{\underline{\lambda}}_{v_j}/2) \frac{1}{m}\sum_{i=1}^m \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) + \frac{1}{m\sigma_v^2}$$

where  $(\boldsymbol{\beta}_{-1}, \sigma_u^2, \sigma_v^2) = [-C_1, C_1]^{p-1} \times [-C_1, C_1] \times [C_1^{-1}, C_1]$ . According to (S2.28), (S2.29), (S2.33), (S2.34), and (S2.37), we obtain

$$\begin{aligned} & \exp(\beta_1^{r0} + U_i)\phi(\boldsymbol{\beta}_{-1}^0) + O_p(n^{-\rho}) \\ &= \exp\left(\beta_1^r + \hat{\underline{\mu}}_{u_i} + \hat{\underline{\lambda}}_{u_i}/2\right)\{\phi(\boldsymbol{\beta}_{-1}) + O_p(n^{-\rho})\} + \frac{\hat{\underline{\mu}}_{u_i}}{n\sigma_u^2}, \quad (S2.40) \end{aligned}$$

where the remainders  $O_p(\cdot)$  are of the stated orders uniformly in  $1 \leq i \leq m$  and in  $(\beta_1^r, \boldsymbol{\beta}_{-1}, \sigma_u^2) \in [-2C_1, 2C_1] \times [-C_1, C_1]^{p-1} \times [C_1^{-1}, C_1]$ . Since (S2.22) implies  $\widehat{\lambda}_{u_i} < \sigma_u^2$ , the right-hand side of (S2.40) equals

$$\begin{aligned} & \{\widehat{\mu}_{u_i}/(n\sigma_u^2)\} + \exp(\beta_1^r + \widehat{\mu}_{u_i} + \widehat{\lambda}_{u_i}/2)\{\phi(\boldsymbol{\beta}_{-1}) + O_p(n^{-\rho})\} \\ = & \{\widehat{\mu}_{u_i}/(n\sigma_u^2)\} + \exp(\mu_i + \omega_i)\{\phi(\boldsymbol{\beta}_{-1}) + O_p(n^{-\rho})\}, \end{aligned} \quad (\text{S2.41})$$

where  $\beta_1^r - \sigma_u^2/2 \leq \omega_i \leq \beta_1^r + \sigma_u^2/2$ . By the assumption (A5),  $|\omega_i|$  is bounded uniformly in  $i$ . Together with uniformly bounded  $|\omega_i|$ , (S2.41), and (S2.40), we can derive that

$$\begin{aligned} & \exp(\beta_1^r + \widehat{\mu}_{u_i} + \widehat{\lambda}_{u_i}/2)\{\phi(\boldsymbol{\beta}_{-1}) + o_p(1)\} \\ = & \exp(\beta_1^{r0} + U_i)\{\phi(\boldsymbol{\beta}_{-1}^0) + o_p(1)\} \end{aligned} \quad (\text{S2.42})$$

uniformly in  $1 \leq i \leq m$  and in  $(\beta_1^r, \boldsymbol{\beta}_{-1}, \sigma_u^2) \in [-2C_1, 2C_1] \times [-C_1, C_1]^{p-1} \times [C_1^{-1}, C_1]$ . The detailed derivations of (S2.42) is similar to the process of getting the equation (4.13) in Hall et al. (2011).

By (S2.25) and (S2.38), we have

$$(n\widehat{\lambda}_{u_i})^{-1} = (n\sigma_u^2)^{-1} + \exp(\beta_1^r + \widehat{\mu}_{u_i} + \widehat{\lambda}_{u_i}/2)\{\phi(\boldsymbol{\beta}_{-1}) + O_p(n^{-\rho})\} \quad (\text{S2.43})$$

uniformly in  $1 \leq i \leq m$  and in  $(\beta_1^r, \boldsymbol{\beta}_{-1}, \sigma_u^2) \in [-2C_1, 2C_1] \times [-C_1, C_1] \times [C_1^{-1}, C_1]$ . Combining (S2.42) and (S2.43) we derive that

$$\widehat{\lambda}_{u_i} = [\sigma_u^{-2} + n \exp(\beta_1^{r0} + U_i)\phi(\boldsymbol{\beta}_{-1}^0)\{1 + o_p(1)\}]^{-1},$$

which implies that  $0 < \widehat{\lambda}_{u_i} < \sigma_u^2$ . Using the fact  $\max_{1 \leq i \leq m} \exp(-U_i) = O(n^\epsilon)$ , we have

$$\widehat{\lambda}_{u_i} = \{n\phi(\beta_{-1}^0) \exp(\beta_1^{r0} + U_i)\}^{-1} + o_p(n^{\epsilon-1}) = O_p(n^{\epsilon-1}). \quad (\text{S2.44})$$

Combining (S2.42) and (S2.44) we have

$$\widehat{\mu}_{u_i} = U_i + \beta_1^{r0} - \beta_1^r + \log \left\{ \frac{\phi(\beta_{-1}^0)}{\phi(\beta_{-1})} \right\} + o_p(1). \quad (\text{S2.45})$$

By (S2.29) and (S2.34), we have

$$\begin{aligned} & \exp(\beta_1^{c0} + V_j) \phi(\beta_{-1}^0) + O_p(m^{-\rho}) \\ &= \exp(\beta_1^c + \widehat{\mu}_{v_j} + \widehat{\lambda}_{v_j}/2) \{\phi(\beta_{-1}) + O_p(n^{-\rho})\} + \frac{\widehat{\mu}_{v_j}}{m\sigma_v^2} \end{aligned} \quad (\text{S2.46})$$

uniformly in  $1 \leq j \leq n$  and in  $(\beta_1^c, \beta_{-1}, \sigma_v^2) \in [-2C_1, 2C_1] \times [-C_1, C_1]^{p-1} \times [C_1^{-1}, C_1]$ . The following properties can be derived by analogy (S2.42), (S2.44), and (S2.46),

$$\begin{aligned} & \exp(\beta_1^c + \widehat{\mu}_{v_j} + \widehat{\lambda}_{v_j}/2) = \exp(\beta_1^{c0} + V_j) \{\phi(\beta_{-1}^0) + o_p(1)\}, \\ & \widehat{\lambda}_{v_j} = \{m\phi(\beta_{-1}^0) \exp(\beta_1^{c0} + V_j)\}^{-1} + o_p(m^{\epsilon-1}) = O_p(m^{\epsilon-1}) \end{aligned} \quad (\text{S2.47})$$

$$\widehat{\mu}_{v_j} = V_j + \beta_1^{c0} - \beta_1^c + \log \left\{ \frac{\phi(\beta_{-1}^0)}{\phi(\beta_{-1})} \right\} + o_p(1). \quad (\text{S2.48})$$

By (S2.19), (S2.21), (S2.45), and (S2.48), we have

$$\beta_1^{r0} - \widehat{\beta}_1^r + \log \left\{ \frac{\phi(\beta_{-1}^0)}{\phi(\widehat{\beta}_{-1})} \right\} = o_p(1), \quad (\text{S2.49})$$

$$\beta_1^{c0} - \widehat{\beta}_1^c + \log \left\{ \frac{\phi(\beta_{-1}^0)}{\phi(\widehat{\beta}_{-1})} \right\} = o_p(1). \quad (\text{S2.50})$$

Combining (S2.5), (S2.35), (S2.36), (S2.40), and (S2.46) we have

$$\begin{aligned}
& \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij} \left\{ Y_{ij} - \exp \left( \mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i} + \frac{1}{2} \lambda_{u_i} \right) \right\} \\
& + \frac{1}{nm} \sum_{j=1}^n \sum_{i=1}^m \mathbf{X}_{ij} \left\{ Y_{ij} - \exp \left( \mathbf{X}_{ij}^T \boldsymbol{\beta}^c + \mu_{v_j} + \frac{1}{2} \lambda_{v_j} \right) \right\} \\
& = 2\phi(\boldsymbol{\beta}_{-1}^0) \left\{ \frac{\phi_1(\boldsymbol{\beta}_{-1}^0)}{\phi(\boldsymbol{\beta}_{-1}^0)} - \frac{\phi_1(\boldsymbol{\beta}_{-1})}{\phi(\boldsymbol{\beta}_{-1})} \right\} \exp \left\{ \beta_1^0 + \frac{(\sigma_u^2)^0}{2} + \frac{(\sigma_v^2)^0}{2} \right\} + o_p(1).
\end{aligned} \tag{S2.51}$$

By the assumption (A9), (S2.51) implies the consistency of  $\widehat{\boldsymbol{\beta}}_{-1}$ . Combining (S2.49) and (S2.50) with (S2.51), respectively, we obtain the consistency of  $\widehat{\boldsymbol{\beta}}_1^r$  and  $\widehat{\boldsymbol{\beta}}_1^c$ .

Note that results (S2.12), (S2.44), and (S2.45) imply

$$\widehat{\underline{\sigma}}_u^2 = \frac{1}{m} \sum_{i=1}^m \left[ U_i + \beta_1^{r0} - \beta_1^r + \log \left\{ \frac{\phi(\boldsymbol{\beta}_{-1}^0)}{\phi(\boldsymbol{\beta}_{-1})} \right\} \right]^2 + o_p(1),$$

by consistency of  $\widehat{\boldsymbol{\beta}}_1^r$  and  $\widehat{\boldsymbol{\beta}}_{-1}$ , and  $m^{-1} \sum_{i=1}^m U_i^2 = (\sigma_u^2)^0 + O_p(m^{-1/2})$ , further we have

$$\widehat{\underline{\sigma}}_u^2 = (\sigma_u^2)^0 + o_p(1), \tag{S2.52}$$

which implies  $\widehat{\underline{\sigma}}_u^2$  is consistent.

For the consistency of  $\widehat{\underline{\sigma}}_v^2$ , it can be derived from the results (S2.13), (S2.47), (S2.48), (S2.49), (S2.50), and  $n^{-1} \sum_{j=1}^n V_j^2 = (\sigma_v^2)^0 + O_p(n^{-1/2})$  analogously:

$$\widehat{\underline{\sigma}}_v^2 = \frac{1}{n} \sum_{j=1}^n V_j^2 + o_p(1) = (\sigma_v^2)^0 + o_p(1). \tag{S2.53}$$

Due to  $\beta_1^{r0} = \beta_1^0 + (\sigma_v^2)^0/2$  and  $\beta_1^{c0} = \beta_1^0 + (\sigma_u^2)^0/2$ , we have

$$\beta_1^0 = \frac{1}{2} \left\{ \beta_1^{r0} - \frac{(\sigma_v^2)^0}{2} + \beta_1^{c0} - \frac{(\sigma_u^2)^0}{2} \right\} \quad (\text{S2.54})$$

and can define the estimator of  $\beta_1^0$  by

$$\widehat{\underline{\beta}}_1 = \frac{1}{2} \left( \widehat{\underline{\beta}}_1^r - \frac{\widehat{\sigma}_v^2}{2} + \widehat{\underline{\beta}}_1^c - \frac{\widehat{\sigma}_u^2}{2} \right). \quad (\text{S2.55})$$

Together, equations (S2.49), (S2.50), (S2.52), (S2.53), (S2.54), and (S2.55)

imply that

$$\widehat{\underline{\beta}}_1 = \beta_1^0 + o_p(1),$$

and  $\beta_1^0$  can be estimated consistently.

## S2.2 Convergence rate for variational estimators

Since (S2.24), (S2.26), and (S2.33) hold, we can define  $\Delta_{i,1}$ ,  $\Delta_{i,2}$ , and  $\Delta_{i,3}$

by

$$\frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) = \phi(\boldsymbol{\beta}_{-1}) \exp\{\Delta_{i,1}(\boldsymbol{\beta}_{-1})\}, \quad (\text{S2.56})$$

$$\frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) = \phi_1(\boldsymbol{\beta}_{-1}) \exp\{\Delta_{i,2}(\boldsymbol{\beta}_{-1})\}, \quad (\text{S2.57})$$

$$\frac{1}{n \exp(\beta_1^{r0})} \left( \sum_{j=1}^n Y_{ij} - \frac{\mu_{u_i}}{\sigma_u^2} \right) = \phi(\boldsymbol{\beta}_{-1}^0) \exp\{U_i + \Delta_{i,3}(\boldsymbol{\beta}^r)\}, \quad (\text{S2.58})$$

uniformly in  $1 \leq i \leq m$ ; since (S2.25), (S2.27), and (S2.34) hold, we can define  $\Delta'_{j,1}$ ,  $\Delta'_{j,2}$ , and  $\Delta'_{j,3}$  by

$$\frac{1}{m} \sum_{i=1}^m \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) = \phi(\boldsymbol{\beta}_{-1}) \exp\{\Delta'_{j,1}(\boldsymbol{\beta}_{-1})\}, \quad (\text{S2.59})$$

$$\frac{1}{m} \sum_{i=1}^m \mathbf{X}_{ij} \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) = \phi_1(\boldsymbol{\beta}_{-1}) \exp\{\Delta'_{j,2}(\boldsymbol{\beta}_{-1})\}, \quad (\text{S2.60})$$

$$\frac{1}{m \exp(\beta_1^{c0})} \left( \sum_{i=1}^m Y_{ij} - \frac{\mu_{v_j}}{\sigma_v^2} \right) = \phi(\boldsymbol{\beta}_{-1}^0) \exp\{V_j + \Delta'_{j,3}(\boldsymbol{\beta}^c)\}, \quad (\text{S2.61})$$

uniformly in  $j$ , and where  $\Delta_{i,1}$ ,  $\Delta_{i,2}$ ,  $\Delta_{i,3}$ ,  $\Delta'_{j,1}$ ,  $\Delta'_{j,2}$ , and  $\Delta'_{j,3}$  satisfy, for all  $C_1 > 0$  and each  $\rho \in (0, 1/2)$ ,

$$\begin{aligned} \max_{1 \leq i \leq n} \sup_{|\beta_1^c|, |\beta_2|, \dots, |\beta_p| \leq C_1} |\Delta_{i,3}(\boldsymbol{\beta}^c)| &= O_p(n^{-\rho}), \\ \max_{1 \leq j \leq m} \sup_{|\beta_1^c|, |\beta_2|, \dots, |\beta_p| \leq C_1} |\Delta'_{j,3}(\boldsymbol{\beta}^c)| &= O_p(m^{-\rho}). \end{aligned}$$

By Taylor series expansion of (S2.56), we have

$$\begin{aligned} & \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) / \phi(\boldsymbol{\beta}_{-1}) \\ &= 1 + \Delta_{i,1}(\boldsymbol{\beta}_{-1}) + \frac{\Delta_{i,1}^2(\boldsymbol{\beta}_{-1})}{2} + O\{\Delta_{i,1}^3(\boldsymbol{\beta}_{-1})\}, \end{aligned} \quad (\text{S2.62})$$

uniformly in  $1 \leq i \leq m$ , then squaring on both sides (S2.62), we have

$$\left\{ \frac{1}{n} \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) / \phi(\boldsymbol{\beta}_{-1}) - 1 \right\}^2 = \Delta_{i,1}^2(\boldsymbol{\beta}_{-1}) + O\{\Delta_{i,1}^3(\boldsymbol{\beta}_{-1})\},$$

which implies that for any  $\epsilon > 0$ ,

$$\max_{1 \leq i \leq m} \sup_{\boldsymbol{\beta}_{-1}: \|\boldsymbol{\beta}_{-1}\| \leq C_1} \Delta_{i,1}^2(\boldsymbol{\beta}_{-1}) = O_p(n^{\epsilon-1}). \quad (\text{S2.63})$$

Combining (S2.63) and

$$\begin{aligned} & \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}) / \phi(\boldsymbol{\beta}_{-1}) - 1 \\ &= \frac{1}{m} \sum_{i=1}^m \Delta_{i,1}(\boldsymbol{\beta}_{-1}) + \frac{1}{m} \sum_{i=1}^m \frac{\Delta_{i,1}^2(\boldsymbol{\beta}_{-1})}{2} + O\{\Delta_{i,1}^3(\boldsymbol{\beta}_{-1})\} \end{aligned}$$

we have

$$\sup_{\boldsymbol{\beta}_{-1} \in [-C_1, C_1]^{p-1}} \frac{1}{m} \left| \sum_{i=1}^m \Delta_{i,1}(\boldsymbol{\beta}_{-1}) \right| = O_p\{(mn)^{\epsilon-1/2} + n^{\epsilon-1}\}. \quad (\text{S2.64})$$

Similar to the derivation process of (S2.64), for any  $\epsilon > 0$ , we have

$$\begin{aligned} \sup_{\boldsymbol{\beta}_{-1} \in [-C_1, C_1]^{p-1}} \frac{1}{m} \left| \sum_{i=1}^m \Delta_{i,2}(\boldsymbol{\beta}_{-1}) \right| &= O_p\{(mn)^{\epsilon-1/2} + n^{\epsilon-1}\}, \quad (\text{S2.65}) \\ \sup_{\boldsymbol{\beta}_{-1} \in [-C_1, C_1]^{p-1}} \frac{1}{n} \left| \sum_{j=1}^n \Delta'_{j,1}(\boldsymbol{\beta}_{-1}) \right| &= O_p\{(mn)^{\epsilon-1/2} + m^{\epsilon-1}\}, \\ \sup_{\boldsymbol{\beta}_{-1} \in [-C_1, C_1]^{p-1}} \frac{1}{n} \left| \sum_{j=1}^n \Delta'_{j,2}(\boldsymbol{\beta}_{-1}) \right| &= O_p\{(mn)^{\epsilon-1/2} + m^{\epsilon-1}\}. \end{aligned}$$

Using Taylor expansion of (S2.58) we have

$$\begin{aligned} & \frac{1}{n} \sum_{j=1}^n Y_{ij} - \frac{\mu_{u_i}}{n\sigma_u^2} \\ &= \phi(\beta_1^0) \exp(U_i + \beta_1^{r0}) \left\{ 1 + \Delta_{i,3}(\boldsymbol{\beta}^r) + \frac{1}{2} \Delta_{i,3}^2(\boldsymbol{\beta}^r) + O_p(\Delta_{i,3}^3(\boldsymbol{\beta}^r)) \right\}. \end{aligned} \quad (\text{S2.66})$$

uniformly in  $1 \leq i \leq m$ . By (S2.45), we have  $\max_{1 \leq i \leq m} |\mu_{u_i}| = O(n^\epsilon)$  for

each  $\epsilon > 0$ . Combining this result and (S2.66) we have

$$\begin{aligned} & \frac{1}{n} \sum_{j=1}^n \phi^{-1}(\beta_1^0) \exp(-U_i - \beta_1^{r0}) Y_{ij} - O(n^{\epsilon-1}) - 1 \\ &= \Delta_{i,3}(\boldsymbol{\beta}^r) + \frac{1}{2} \Delta_{i,3}^2(\boldsymbol{\beta}^r) + O_p\{\Delta_{i,3}^3(\boldsymbol{\beta}^r)\}. \end{aligned} \quad (\text{S2.67})$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Squaring on both sides (S2.67) we have

$$\begin{aligned} & \left\{ \frac{1}{n} \sum_{j=1}^n \phi^{-1}(\beta_{-1}^0) \exp(-U_i - \beta_1^{r0}) Y_{ij} - O_p(n^{\epsilon-1}) - 1 \right\}^2 \\ &= \Delta_{i,3}^2(\beta^r) + O_p\{\Delta_{i,3}^3(\beta^r)\} \end{aligned} \quad (\text{S2.68})$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Using the fact

$$E \left\{ \frac{1}{n} \sum_{j=1}^n \phi^{-1}(\beta_{-1}^0) \exp(-U_i - \beta_1^{r0}) Y_{ij} - 1 \right\}^2 = O_p(n^{-1}),$$

and (S2.68) we have

$$\max_{1 \leq i \leq m} \sup_{|\beta_1^r| \leq 2C_1, \beta_{-1}^0 \in [-C_1, C_1]^{p-1}} O\{\Delta_{i,3}^2(\beta^r)\} = O_p(n^{\epsilon-1}).$$

Combining the facts

$$E \left\{ \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \phi^{-1}(\beta_{-1}^0) \exp(-U_i - \beta_1^{r0}) Y_{ij} - 1 \right\}^2 = O\{(mn)^{-1}\} + O(n^{-1}),$$

and

$$\begin{aligned} & \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \phi^{-1}(\beta_{-1}^0) \exp(-U_i - \beta_1^{r0}) Y_{ij} - O(n^{\epsilon-1}) - 1 \\ &= \frac{1}{m} \sum_{i=1}^m \Delta_{i,3}(\beta^r) + \frac{1}{m} \sum_{i=1}^m \frac{\Delta_{i,3}^2(\beta^r)}{2} + O_p\{\Delta_{i,3}^3(\beta^r)\}, \end{aligned}$$

we have

$$\begin{aligned} & \sup_{|\beta_1^r| \leq 2C_1, \beta_{-1}^0 \in [-C_2, C_2]^{p-1}} \frac{1}{m} \left| \sum_{i=1}^m \Delta_{i,3}(\beta^r) \right| \\ &= O_p\{n^{-1/2} + (mn)^{\epsilon-1/2}\}, \end{aligned} \quad (\text{S2.69})$$

for each  $\epsilon > 0$ . Similar to derivation of (S2.69), we can obtain

$$\begin{aligned} & \sup_{|\beta_1^r| \leq 2C_1, \beta_{-1} \in [-C_2, C_2]^{p-1}} \frac{1}{n} \left| \sum_{j=1}^n \Delta'_{j,3}(\beta_1^c, \beta_1) \right| \\ &= O_p\{m^{-1/2} + (mn)^{\epsilon-1/2}\}, \end{aligned} \quad (\text{S2.70})$$

for each  $\epsilon > 0$ .

By the notation of (S2.56)-(S2.61), (S2.37) is equivalent to

$$\begin{aligned} & \exp \left\{ \beta_1^r + \hat{\underline{\mu}}_{u_i} + \frac{1}{2} \hat{\underline{\lambda}}_{u_i} + \Delta_{i,1}(\beta_{-1}) \right\} \phi(\beta_{-1}) \\ &= \exp\{\beta_1^{r0} + U_i + \Delta_{i,3}(\beta^r)\} \phi(\beta_{-1}^0), \end{aligned} \quad (\text{S2.71})$$

uniformly in  $1 \leq i \leq m$ , and (S2.39) is equivalent to

$$\begin{aligned} & \exp \left\{ \beta_1^c + \hat{\underline{\mu}}_{v_j} + \frac{1}{2} \hat{\underline{\lambda}}_{v_j} + \Delta_{j,1}(\beta_{-1}) \right\} \phi(\beta_1) \\ &= \exp\{\beta_1^{c0} + V_j + \Delta'_{j,3}(\beta^c)\} \phi(\beta_{-1}^0). \end{aligned} \quad (\text{S2.72})$$

uniformly in  $1 \leq j \leq n$ . Taking logarithms of both sides of (S2.71) and (S2.72), respectively, we have

$$\begin{aligned} & \beta_1^r - \beta_1^{r0} + \log \left\{ \frac{\phi(\beta_{-1})}{\phi(\beta_{-1}^0)} \right\} \\ &= U_i - \hat{\underline{\mu}}_{u_i} - \frac{1}{2} \hat{\underline{\lambda}}_{u_i} + \Delta_{i,3}(\beta^r) - \Delta_{i,1}(\beta_{-1}), \end{aligned} \quad (\text{S2.73})$$

uniformly in  $1 \leq i \leq m$ , and

$$\begin{aligned} & \beta_1^c - \beta_1^{c0} + \log \left\{ \frac{\phi(\beta_{-1})}{\phi(\beta_{-1}^0)} \right\} \\ &= V_j - \hat{\underline{\mu}}_{v_j} - \frac{1}{2} \hat{\underline{\lambda}}_{v_j} + \Delta'_{j,3}(\beta^c) - \Delta'_{j,1}(\beta_{-1}). \end{aligned} \quad (\text{S2.74})$$

uniformly in  $1 \leq j \leq m$ . Adding (S2.73) over  $i$  and adding (S2.74) over  $j$ ,

$\beta_1^r, \beta_1^c, \beta_{-1}$  satisfy the following equations,

$$\begin{aligned} & \beta_1^r - \beta_1^{r0} + \log \left\{ \frac{\phi(\beta_{-1})}{\phi(\beta_{-1}^0)} \right\} \\ = & \frac{1}{m} \sum_{i=1}^m \left\{ U_i - \hat{\mu}_{u_i} - \frac{1}{2} \hat{\lambda}_{u_i} + \Delta_{i,3}(\beta^r) - \Delta_{i,1}(\beta_{-1}) \right\}, \\ & \beta_1^c - \beta_1^{c0} + \log \left\{ \frac{\phi(\beta_{-1})}{\phi(\beta_{-1}^0)} \right\} \\ = & \frac{1}{n} \sum_{j=1}^n \left\{ V_j - \hat{\mu}_{v_j} - \frac{1}{2} \hat{\lambda}_{v_j} + \Delta'_{j,3}(\beta^c) - \Delta'_{j,1}(\beta_{-1}) \right\}. \end{aligned}$$

By  $m^{-1} \sum_{i=1}^m U_i = O_p(m^{-1/2})$ , (S2.19), (S2.44), and the following property,

$$\begin{aligned} & \sup_{|\beta_1^r| \leq C_1, \beta_{-1} \in [-C_1, C_1]} \frac{1}{m} \left| \sum_{i=1}^m \{ \Delta_{i,3}(\beta^0) - \Delta_{i,1}(\beta_{-1}) \} \right| \\ = & O_p\{m^{-1/2} + (mn)^{\epsilon-1/2}\}, \end{aligned} \quad (\text{S2.75})$$

which can be derived from (S2.64) and (S2.68), we have

$$\widehat{\beta}_{-1}^r - \beta_1^{r0} + \log \left\{ \frac{\phi(\widehat{\beta}_{-1})}{\phi(\beta_{-1}^0)} \right\} = O_p(m^{-1/2} + n^{-1/2}). \quad (\text{S2.76})$$

By  $n^{-1} \sum_{j=1}^n V_j = O_p(n^{-1/2})$ , (S2.21), (S2.47), and the following property,

$$\begin{aligned} & \sup_{\beta \in [-C_1, C_1]^p} \frac{1}{n} \left| \sum_{j=1}^n \{ \Delta'_{j,3}(\beta^{r0}) - \Delta'_{j,1}(\beta_{-1}) \} \right| \\ = & O_p\{m^{-1/2} + (mn)^{\epsilon-1/2}\}, \end{aligned} \quad (\text{S2.77})$$

which can be derived from (S2.65) and (S2.69), we have

$$\widehat{\beta}_{-1}^c - \beta_1^{c0} + \log \left\{ \frac{\phi(\widehat{\beta}_{-1})}{\phi(\beta_{-1}^0)} \right\} = O_p(m^{-1/2} + n^{-1/2}). \quad (\text{S2.78})$$

Define

$$\Delta_r = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij} \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} + U_i)\}, \quad (\text{S2.79})$$

and

$$\Delta_c = \frac{1}{nm} \sum_{j=1}^n \sum_{i=1}^m \mathbf{X}_{ij} \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{c0} + V_j)\}. \quad (\text{S2.80})$$

Since the variance of  $\Delta_r$  is

$$\begin{aligned} \text{var}(\Delta_r) &= \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n E[\mathbf{X}_{ij,-1}^T \mathbf{X}_{ij,-1} \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} + U_i)\}^2] \\ &\quad + \frac{1}{m^2 n^2} \sum_{i=1}^m \sum_{j=1}^n \sum_{l \neq j}^n E[\mathbf{X}_{ij,-1}^T \mathbf{X}_{il,-1} \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} + U_i)\} \\ &\quad \times \{Y_{il} - \exp(\mathbf{X}_{il}^T \boldsymbol{\beta}^{r0} + U_i)\}] \\ &\quad + \frac{1}{m^2 n^2} \sum_{i=1}^m \sum_{j=1}^n \sum_{k \neq i}^m E[\mathbf{X}_{ij,-1}^T \mathbf{X}_{kj,-1} \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} + U_i)\} \\ &\quad \times \{Y_{kj} - \exp(\mathbf{X}_{kj}^T \boldsymbol{\beta}^{r0} + U_k)\}] \\ &= \frac{1}{m^2 n^2} \text{I} + \frac{1}{m^2 n^2} \text{II} + \frac{1}{m^2 n^2} \text{III}, \end{aligned}$$

where

$$\begin{aligned} \text{I} &= \sum_{i=1}^m \sum_{j=1}^n E[\mathbf{X}_{ij,-1}^T \mathbf{X}_{ij,-1} \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} + U_i)\}^2] \\ &= mn \phi_2(\boldsymbol{\beta}_{-1}^0) \exp\{\beta_1^0 + (\sigma_u^2)^0/2 + (\sigma_v^2)^0/2\} \\ &\quad + mn \phi_2(2\boldsymbol{\beta}_{-1}^0) \exp\{2\beta_1^0 + 2(\sigma_u^2)^0 + (\sigma_v^2)^0\} [\exp\{(\sigma_v^2)^0\} - 1] \\ &= O(mn), \end{aligned} \quad (\text{S2.81})$$

II (S2.82)

$$\begin{aligned}
 &= \sum_{i=1}^m \sum_{j=1}^n \sum_{l \neq j}^n E[\mathbf{X}_{ij,-1}^T \mathbf{X}_{il,-1} \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} + U_i)\} \\
 &\quad \times \{Y_{il} - \exp(\mathbf{X}_{il}^T \boldsymbol{\beta}^{r0} + U_i)\}] \\
 &= \sum_{i=1}^m \sum_{j=1}^n \sum_{l \neq j}^n \phi_1^2(\boldsymbol{\beta}_{-1}^0) \exp\{2(\sigma_u^2)^0\} E[\{\exp(\beta_1^0 + V_j) - \exp(\beta_1^{r0})\} \\
 &\quad \times \{\exp(\beta_1^0 + V_l) - \exp(\beta_1^{r0})\}] \\
 &= 0, \tag{S2.83}
 \end{aligned}$$

and

III

$$\begin{aligned}
 &= \sum_{i=1}^m \sum_{j=1}^n \sum_{k \neq i}^m E[\mathbf{X}_{ij,-1}^T \mathbf{X}_{kj,-1} \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} + U_i)\} \\
 &\quad \times \{Y_{kj} - \exp(\mathbf{X}_{kj}^T \boldsymbol{\beta}^{r0} + U_k)\}] \\
 &= \sum_{i=1}^m \sum_{j=1}^n \sum_{k \neq i}^m E[\mathbf{X}_{ij,-1}^T \mathbf{X}_{kj,-1} E[\{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} + U_i)\} \\
 &\quad \times \{Y_{kj} - \exp(\mathbf{X}_{kj}^T \boldsymbol{\beta}^{r0} + U_k)\} | \mathbf{X}_{ij}, \mathbf{X}_{kj}, U_i, U_k, V_j]] \\
 &= \sum_{i=1}^m \sum_{j=1}^n \sum_{k \neq i}^m E[\mathbf{X}_{ij,-1}^T \mathbf{X}_{kj,-1} \{\exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + U_i + V_j) - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} + U_i)\} \\
 &\quad \times \{\exp(\mathbf{X}_{kj}^T \boldsymbol{\beta}^0 + U_k + V_j) - \exp(\mathbf{X}_{kj}^T \boldsymbol{\beta}^{r0} + U_k)\}] \\
 &= m(m-1)n\phi_1^2(\boldsymbol{\beta}_{-1}^0) \exp\{2\beta_1^0 + (\sigma_u^2)^0 + (\sigma_v^2)^0\} [\exp\{(\sigma_v^2)^0\} - 1] \\
 &= O\{m(m-1)n\}. \tag{S2.84}
 \end{aligned}$$

Combining (S2.79), (S2.81), (S2.83), and (S2.84) we have

$$\Delta_r = O_p(n^{-1/2}).$$

The bound of  $\Delta_c$  can be derived analogously,

$$\Delta_c = O_p(m^{-1/2}).$$

Setting (S2.5) equal to zero we have

$$\begin{aligned} & \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1}^T \left\{ Y_{ij} - \exp \left( \mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i} + \frac{1}{2} \lambda_{u_i} \right) \right\} \\ & + \frac{1}{nm} \sum_{j=1}^n \sum_{i=1}^m \mathbf{X}_{ij,-1}^T \left\{ Y_{ij} - \exp \left( \mathbf{X}_{ij}^T \boldsymbol{\beta}^c + \mu_{v_j} + \frac{1}{2} \lambda_{v_j} \right) \right\} = 0. \end{aligned} \quad (\text{S2.85})$$

By (S2.57), (S2.60), (S2.79), and (S2.80), (S2.86) is equivalent to

$$\begin{aligned} & \Delta_r + \exp(\beta_1^{r0}) \phi_1(\boldsymbol{\beta}_{-1}^0) \frac{1}{m} \sum_{i=1}^m \exp\{U_i + \Delta_{i,2}(\boldsymbol{\beta}_{-1}^0)\} \\ & + \Delta_c + \exp(\beta_1^{c0}) \phi_1(\boldsymbol{\beta}_{-1}^0) \frac{1}{n} \sum_{j=1}^n \exp\{V_j + \Delta'_{j,2}(\boldsymbol{\beta}_{-1}^0)\} \\ = & \exp(\beta_1^r) \phi_1(\boldsymbol{\beta}_{-1}) \frac{1}{m} \sum_{i=1}^m \exp \left\{ \mu_{u_i} + \frac{1}{2} \lambda_{u_i} + \Delta_{i,2}(\boldsymbol{\beta}_{-1}) \right\} \\ & + \exp(\beta_1^c) \phi_1(\boldsymbol{\beta}_{-1}) \frac{1}{n} \sum_{j=1}^n \exp \left\{ \mu_{v_j} + \frac{1}{2} \lambda_{v_j} + \Delta'_{j,2}(\boldsymbol{\beta}_{-1}) \right\} \end{aligned} \quad (\text{S2.86})$$

By equations (S2.71) and (S2.72), respectively,

$$\widehat{\underline{\mu}}_{u_i} + \frac{1}{2} \widehat{\underline{\lambda}}_{u_i} \quad (\text{S2.87})$$

$$= \beta_1^{r0} - \widehat{\underline{\beta}}_1^r + \log \left\{ \frac{\phi(\boldsymbol{\beta}_{-1}^0)}{\phi(\widehat{\underline{\beta}}_{-1})} \right\} + U_i + \Delta_{i,3}(\widehat{\underline{\beta}}^r) - \Delta_{i,1}(\widehat{\underline{\beta}}_{-1}),$$

$$\widehat{\underline{\mu}}_{v_j} + \frac{1}{2} \widehat{\underline{\lambda}}_{v_j} \quad (\text{S2.88})$$

$$= \beta_1^{c0} - \widehat{\underline{\beta}}_1^c + \log \left\{ \frac{\phi(\boldsymbol{\beta}_{-1}^0)}{\phi(\widehat{\underline{\beta}}_{-1})} \right\} + V_j + \Delta'_{j,3}(\widehat{\underline{\beta}}^c) - \Delta'_{j,1}(\widehat{\underline{\beta}}_{-1}),$$

we have the derivations of the two exponential terms on the right of (S2.86),

$$\exp \left\{ \hat{\underline{\mu}}_{u_i} + \frac{1}{2} \hat{\underline{\lambda}}_{u_i} + \Delta_{i,2}(\hat{\underline{\beta}}_{-1}) \right\} \quad (\text{S2.89})$$

$$= \exp \left\{ \beta_1^{r0} - \hat{\underline{\beta}}_1^r + U_i + \Delta_{i,3}(\hat{\underline{\beta}}^r) - \Delta_{i,1}(\hat{\underline{\beta}}_{-1}) + \Delta_{i,2}(\hat{\underline{\beta}}_{-1}) \right\} \frac{\phi(\beta_{-1}^0)}{\phi(\hat{\underline{\beta}}_{-1})},$$

$$\exp \left\{ \hat{\underline{\mu}}_{v_j} + \frac{1}{2} \hat{\underline{\lambda}}_{v_j} + \Delta_{j,2}(\hat{\underline{\beta}}_1) \right\} \quad (\text{S2.90})$$

$$= \exp \left\{ \beta_1^{c0} - \hat{\underline{\beta}}_1^c + V_j + \Delta'_{j,3}(\hat{\underline{\beta}}^c) - \Delta'_{j,1}(\hat{\underline{\beta}}_{-1}) + \Delta'_{j,2}(\hat{\underline{\beta}}_{-1}) \right\} \frac{\phi(\beta_{-1}^0)}{\phi(\hat{\underline{\beta}}_{-1})}.$$

Combining (S2.86), (S2.89), and (S2.90) we have

$$\begin{aligned} & \Delta_r \phi(\beta_{-1}^0)^{-1} + \exp(\beta_1^{r0}) \frac{\phi_1(\beta_{-1}^0)}{\phi(\beta_{-1}^0)} \frac{1}{m} \sum_{i=1}^m \exp\{U_i + \Delta_{i,2}(\beta_{-1}^0)\} \\ & + \Delta_c \phi(\beta_{-1}^0)^{-1} + \exp(\beta_1^{c0}) \frac{\phi_1(\beta_{-1}^0)}{\phi(\beta_{-1}^0)} \frac{1}{n} \sum_{j=1}^n \exp\{V_j + \Delta'_{j,2}(\beta_{-1}^0)\} \quad (\text{S2.91}) \\ & = \exp(\hat{\underline{\beta}}_1^r) \frac{\phi_1(\beta_{-1})}{\phi(\hat{\underline{\beta}}_{-1})} \\ & \times \frac{1}{m} \sum_{i=1}^m \exp \left\{ \beta_1^{r0} - \hat{\underline{\beta}}_1^r + U_i + \Delta_{i,3}(\hat{\underline{\beta}}^r) - \Delta_{i,1}(\hat{\underline{\beta}}_{-1}) + \Delta_{i,2}(\hat{\underline{\beta}}_{-1}) \right\} \\ & + \exp(\hat{\underline{\beta}}_1^c) \frac{\phi_1(\beta_{-1})}{\phi(\hat{\underline{\beta}}_{-1})} \\ & \times \frac{1}{n} \sum_{j=1}^n \exp \left\{ \beta_1^{c0} - \hat{\underline{\beta}}_1^c + V_j + \Delta'_{j,3}(\hat{\underline{\beta}}^c) - \Delta'_{j,1}(\hat{\underline{\beta}}_{-1}) + \Delta'_{j,2}(\hat{\underline{\beta}}_{-1}) \right\}, \end{aligned}$$

By (S2.79), (S2.80), (S2.75), (S2.77), and (S2.91), we have

$$\begin{aligned} & \frac{\phi_1(\beta_{-1}^0)}{\phi(\beta_{-1}^0)} \left\{ \exp(\beta_1^{r0}) \frac{1}{m} \sum_{i=1}^m \exp(U_i) + \exp(\beta_1^{c0}) \frac{1}{n} \sum_{j=1}^n \exp(V_j) \right\} \\ & = \frac{\phi_1(\hat{\underline{\beta}}_{-1})}{\phi(\hat{\underline{\beta}}_{-1})} \left\{ \exp(\hat{\underline{\beta}}_1^r) \frac{1}{m} \sum_{i=1}^m \exp(U_i) + \exp(\hat{\underline{\beta}}_1^c) \frac{1}{n} \sum_{j=1}^n \exp(V_j) \right\} \\ & + O_p(n^{-1/2} + m^{-1/2}). \quad (\text{S2.92}) \end{aligned}$$

Substituting  $\exp(\widehat{\underline{\beta}}_1^r) = \exp(\beta_1^r)\{1 + (\widehat{\underline{\beta}}_1^r - \beta_1^r) + O_p(\widehat{\underline{\beta}}_1^r - \beta_1^r)\}$  and  $\exp(\widehat{\underline{\beta}}_1^c) = \exp(\beta_1^c)\{1 + (\widehat{\underline{\beta}}_1^c - \beta_1^c) + O_p(\widehat{\underline{\beta}}_1^c - \beta_1^c)\}$  into equation (S2.92), we have

$$\begin{aligned} & \frac{\phi_1(\underline{\beta}_{-1}^0)}{\phi(\underline{\beta}_{-1}^0)} \left\{ \exp(\beta_1^{r0}) \frac{1}{m} \sum_{i=1}^m \exp(U_i) + \exp(\beta_1^{c0}) \frac{1}{n} \sum_{j=1}^n \exp(V_j) \right\} \\ = & \frac{\phi_1(\widehat{\underline{\beta}}_{-1})}{\phi(\widehat{\underline{\beta}}_{-1})} \left\{ \exp(\beta_1^{r0}) \frac{1}{m} \sum_{i=1}^m \exp(U_i) + \exp(\beta_1^{c0}) \frac{1}{n} \sum_{j=1}^n \exp(V_j) \right\} \\ & + O_p(n^{-1/2} + m^{-1/2}), \end{aligned}$$

which implies that

$$\phi_1(\underline{\beta}_{-1}^0) \phi(\underline{\beta}_{-1}^0)^{-1} = \phi_1(\widehat{\underline{\beta}}_{-1}) \phi(\widehat{\underline{\beta}}_{-1})^{-1} + O_p(m^{-1/2} + n^{-1/2}).$$

By the invertible mapping  $\phi'(\cdot)/\phi(\cdot)$  and continuous mapping theorem, we have

$$\widehat{\underline{\beta}}_{-1} = \underline{\beta}_{-1}^0 + O_p(m^{-1/2} + n^{-1/2}). \quad (\text{S2.93})$$

Combining (S2.76), (S2.78), and (S2.93) we have

$$\widehat{\underline{\beta}}_1^r = \beta_1^{r0} + O_p(m^{-1/2} + n^{-1/2}), \quad (\text{S2.94})$$

$$\widehat{\underline{\beta}}_1^c = \beta_1^{c0} + O_p(m^{-1/2} + n^{-1/2}). \quad (\text{S2.95})$$

Combining (S2.87), (S2.93), and (S2.94) we have

$$\widehat{\underline{\mu}}_{u_i} = U_i + \Delta_{i,3}(\widehat{\underline{\beta}}^r) - \Delta_{i,1}(\widehat{\underline{\beta}}_{-1}) + O_p(m^{-1/2} + n^{-1/2}), \quad (\text{S2.96})$$

uniformly in  $1 \leq i \leq m$ . Together with (S2.75) and (S2.96) imply that

$$\begin{aligned} \frac{1}{m} \sum_{i=1}^m \widehat{\underline{\mu}}_{u_i}^2 &= \frac{1}{m} \sum_{i=1}^m U_i^2 + O_p(m^{-1/2} + n^{-1/2}) \\ &= (\sigma_u^2)^0 + O_p(m^{-1/2} + n^{-1/2}). \end{aligned} \quad (\text{S2.97})$$

And combining (S2.88), (S2.93), and (S2.95) we have

$$\widehat{\underline{\mu}}_{v_j} = V_j + \Delta'_{j,3}(\widehat{\underline{\beta}}^c) - \Delta'_{j,1}(\widehat{\underline{\beta}}_{-1}) + O_p(m^{-1/2} + n^{-1/2}), \quad (\text{S2.98})$$

uniformly in  $1 \leq j \leq m$ . Equations (S2.77) and (S2.98) imply that

$$\begin{aligned} \frac{1}{n} \sum_{j=1}^n \widehat{\underline{\mu}}_{v_j}^2 &= \frac{1}{n} \sum_{j=1}^n V_j^2 + O_p(m^{-1/2} + n^{-1/2}) \\ &= (\sigma_v^2)^0 + O_p(m^{-1/2} + n^{-1/2}). \end{aligned} \quad (\text{S2.99})$$

Combining (S2.12), (S2.44), and (S2.97) we have

$$\widehat{\underline{\sigma}}_u^2 = (\sigma_u^2)^0 + O_p(m^{-1/2} + n^{-1/2}), \quad (\text{S2.100})$$

and combinig (S2.13), (S2.47), and (S2.99), we have

$$\widehat{\underline{\sigma}}_v^2 = (\sigma_v^2)^0 + O_p(m^{-1/2} + n^{-1/2}). \quad (\text{S2.101})$$

Together, (S2.94), (S2.95), (S2.100), (S2.101), (S2.54), and (S2.55) give

$$\begin{aligned} \widehat{\underline{\beta}}_{-1} - \beta_1^0 &= \frac{1}{2} \left( \widehat{\underline{\beta}}_{-1}^r - \beta_1^{r0} - \frac{\widehat{\underline{\sigma}}_v^2 - (\sigma_v^2)^0}{2} + \widehat{\underline{\beta}}_{-1}^c - \beta_1^{c0} - \frac{\widehat{\underline{\sigma}}_u^2 - (\sigma_u^2)^0}{2} \right) \\ &= O_p(m^{-1/2} + n^{-1/2}). \end{aligned}$$

This completes the proof of consistency at rate  $m^{-1/2} + n^{-1/2}$  for the Poisson regression model in Theorem 1.

### S3 Proof of Theorem 2 for the Poisson regression model

The proof of Theorem 2 includes 7 steps:

Step1. formulas for estimators in §S3.1 ;

Step2. initial approximation to  $\widehat{\underline{\beta}}_1^r - \beta_1^{r0}$ ,  $\widehat{\underline{\beta}}_1^c - \beta_1^{c0}$ , and  $\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0$  in §S3.2;

Step3. approximate formulae for  $U_i$ ,  $\widehat{\lambda}_{u_i}$ ,  $V_j$ , and  $\widehat{\lambda}_{v_j}$  in §S3.3;

Step4. approximations to  $\zeta_{u_i}$  and  $\zeta_{v_j}$  in §S3.4;

Step5. final approximations to  $\sigma_u^2 - (\sigma_u^2)^0$  and  $\sigma_v^2 - (\sigma_v^2)^0$  in §S3.5;

Step6. approximations to  $\xi_{u_i}$ ,  $\eta_{u_i}$ ,  $\xi_{v_j}$ , and  $\eta_{v_j}$  in §S3.6;

Step7. final approximations to  $\widehat{\underline{\beta}}_1 - \beta_1^0$  and  $\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0$  in §S3.7.

We first derive the initial approximation to  $\widehat{\underline{\beta}}_1^r - \beta_1^{r0}$ ,  $\widehat{\underline{\beta}}_1^c - \beta_1^{c0}$ , and  $\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0$ , and get the remainder terms of them , then control the remainder terms in §S3.2, §S3.3, §S3.5, and §S3.6. At last, §S3.4 and §S3.7 prove the asymptotic results of theorem by the results of remainder terms.

#### S3.1 Formulas for estimators

Based on the consistency results, we define  $\xi_{u_i}$ ,  $\eta_{u_i}$ , and  $\zeta_{u_i}$  by, respectively,

$$\begin{aligned} & \frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} + V_j) \\ = & \phi_1(\boldsymbol{\beta}_{-1}^0) \exp\{(\sigma_v^2)^0/2\} \exp(\xi_{u_i}), \end{aligned} \quad (\text{S3.102})$$

$$\begin{aligned}
& \frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij,-1}^T \hat{\underline{\boldsymbol{\beta}}}_{-1}) \\
&= \phi_1(\hat{\underline{\boldsymbol{\beta}}}_{-1}) \exp(\eta_{u_i}),
\end{aligned} \tag{S3.103}$$

and

$$\begin{aligned}
& \exp\left(\widehat{\underline{\beta}}_{-1}^r + \hat{\underline{\mu}}_{u_i} + \frac{1}{2}\widehat{\underline{\lambda}}_{u_i}\right) \frac{1}{n} \sum_{j=1}^n \left\{ \exp(\mathbf{X}_{ij,-1}^T \hat{\underline{\boldsymbol{\beta}}}_{-1}) - \phi(\hat{\underline{\boldsymbol{\beta}}}_{-1}) \right\} + \frac{\hat{\underline{\mu}}_{u_i}}{n\widehat{\underline{\sigma}}_u^2} \\
&= \frac{1}{n} \sum_{j=1}^n \left\{ Y_{ij} - \exp(\beta_1^{r0} + U_i) \phi(\boldsymbol{\beta}_{-1}^0) \right\} \\
& \quad + \exp(\beta_1^{r0} + U_i) \phi(\boldsymbol{\beta}_{-1}^0) \{1 - \exp(\zeta_{u_i})\},
\end{aligned} \tag{S3.104}$$

uniformly in  $1 \leq i \leq m$ ; define  $\xi_{v_j}$ ,  $\eta_{v_j}$ , and  $\zeta_{v_j}$  by,

$$\begin{aligned}
& \frac{1}{m} \sum_{i=1}^m \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0 + U_i) \\
&= \phi_1(\boldsymbol{\beta}_{-1}^0) \exp\{(\sigma_u^2)^0/2\} \exp(\xi_{v_j}),
\end{aligned} \tag{S3.105}$$

$$\begin{aligned}
& \frac{1}{m} \sum_{i=1}^m \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij,-1}^T \hat{\underline{\boldsymbol{\beta}}}_{-1}) \\
&= \phi_1(\hat{\underline{\boldsymbol{\beta}}}_{-1}) \exp(\eta_{v_j}),
\end{aligned} \tag{S3.106}$$

and

$$\begin{aligned}
& \exp\left(\widehat{\underline{\beta}}_{-1}^c + \hat{\underline{\mu}}_{v_j} + \frac{1}{2}\widehat{\underline{\lambda}}_{v_j}\right) \frac{1}{m} \sum_{i=1}^m \left\{ \exp(\mathbf{X}_{ij,-1}^T \hat{\underline{\boldsymbol{\beta}}}_{-1}) - \phi(\hat{\underline{\boldsymbol{\beta}}}_{-1}) \right\} + \frac{\hat{\underline{\mu}}_{v_j}}{m\widehat{\underline{\sigma}}_v^2} \\
&= \frac{1}{m} \sum_{i=1}^m \left\{ Y_{ij} - \exp(\beta_1^{c0} + V_j) \phi(\boldsymbol{\beta}_{-1}^0) \right\} \\
& \quad + \exp(\beta_1^{c0} + V_j) \phi(\boldsymbol{\beta}_{-1}^0) \{1 - \exp(\zeta_{v_j})\},
\end{aligned} \tag{S3.107}$$

uniformly in  $1 \leq j \leq n$ . By equations (S2.79) and (S2.80), (S2.5) is equivalent to

$$\begin{aligned}
& 2\Delta + \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + U_i + V_j) \\
& + \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + U_i + V_j) \quad (\text{S3.108}) \\
= & \exp(\widehat{\underline{\beta}}_{-1}^r) \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} \exp \left( \mathbf{X}_{ij,-1}^T \widehat{\underline{\beta}}_{-1} + \widehat{\underline{\mu}}_{u_i} + \frac{1}{2} \widehat{\underline{\lambda}}_{u_i} \right) \\
& + \exp(\widehat{\underline{\beta}}_{-1}^c) \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} \exp \left( \mathbf{X}_{ij,-1}^T \widehat{\underline{\beta}}_{-1} + \widehat{\underline{\mu}}_{v_j} + \frac{1}{2} \widehat{\underline{\lambda}}_{v_j} \right),
\end{aligned}$$

where

$$\Delta = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} \{Y_{ij} - \exp(\mathbf{X}_{ij} \boldsymbol{\beta} + U_i + V_j)\},$$

using the notation in (S3.102)-(S3.107), we can write (S3.108) as

$$\begin{aligned}
& 2\Delta + \phi_1(\boldsymbol{\beta}_{-1}^0) \frac{1}{m} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i + \xi_{u_i}) \\
& + \phi_1(\boldsymbol{\beta}_{-1}^0) \frac{1}{n} \sum_{j=1}^n \exp(\beta_1^{c0} + V_j + \xi_{v_j}) \\
= & \phi_1(\widehat{\underline{\beta}}_{-1}) \frac{1}{m} \sum_{i=1}^m \exp \left( \widehat{\underline{\beta}}_{-1}^r + \widehat{\underline{\mu}}_{u_i} + \frac{1}{2} \widehat{\underline{\lambda}}_{u_i} + \eta_{u_i} \right) \\
& + \phi_1(\widehat{\underline{\beta}}_{-1}) \frac{1}{n} \sum_{j=1}^n \exp \left( \widehat{\underline{\beta}}_{-1}^c + \widehat{\underline{\mu}}_{v_j} + \frac{1}{2} \widehat{\underline{\lambda}}_{v_j} + \eta_{v_j} \right), \quad (\text{S3.109})
\end{aligned}$$

and write (S2.8) and (S2.10) as

$$\begin{aligned} & \exp\left(\widehat{\beta}_{-1}^r + \widehat{\mu}_{u_i} + \frac{1}{2}\widehat{\lambda}_{u_i}\right) \phi(\widehat{\beta}_{-1}) \\ = & \exp(\beta_1^{r0} + U_i + \zeta_{u_i}) \phi(\beta_{-1}^0), \end{aligned} \quad (\text{S3.110})$$

$$\begin{aligned} & \exp\left(\widehat{\beta}_{-1}^c + \widehat{\mu}_{v_j} + \frac{1}{2}\widehat{\lambda}_{v_j}\right) \phi(\widehat{\beta}_{-1}) \\ = & \exp(\beta_1^{c0} + V_j + \zeta_{v_j}) \phi(\beta_{-1}^0). \end{aligned} \quad (\text{S3.111})$$

Substituting (S3.110) and (S3.111) into (S3.109) we obtain

$$\begin{aligned} & \frac{2\Delta}{\phi(\beta_{-1}^0)} + \frac{\phi_1(\beta_{-1}^0)}{\phi(\beta_{-1}^0)} \frac{1}{m} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i + \xi_{u_i}) \\ & + \frac{\phi_1(\beta_{-1}^0)}{\phi(\beta_{-1}^0)} \frac{1}{n} \sum_{j=1}^n \exp(\beta_1^{c0} + V_j + \xi_{v_j}) \\ = & \frac{\phi_1(\widehat{\beta}_{-1})}{\phi(\widehat{\beta}_{-1})} \frac{1}{m} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i + \eta_{u_i} + \zeta_{u_i}) \\ & + \frac{\phi_1(\widehat{\beta}_{-1})}{\phi(\widehat{\beta}_{-1})} \frac{1}{n} \sum_{j=1}^n \exp(\beta_1^{c0} + V_j + \eta_{v_j} + \zeta_{v_j}), \end{aligned} \quad (\text{S3.112})$$

### S3.2 Initial approximation to $\widehat{\beta}_{-1}^r - \beta_1^{r0}$ , $\widehat{\beta}_{-1}^c - \beta_1^{c0}$ and $\widehat{\beta}_{-1} - \beta_{-1}^0$

To derive the approximation to  $\widehat{\beta}_{-1} - \beta_{-1}^0$ , write  $\gamma(\beta_{-1}) = \phi_1(\beta_{-1})/\phi(\beta_{-1})$ ,

we have

$$\begin{aligned} \gamma(\widehat{\beta}_{-1}) &= \gamma(\beta_{-1}^0) + \gamma'(\beta_{-1}^0)(\widehat{\beta}_{-1} - \beta_{-1}^0) + O_p\{\|\widehat{\beta}_{-1} - \beta_{-1}^0\|^2\} \\ &= \gamma(\beta_{-1}^0) + \{1 + O_p(m^{-1/2} + n^{-1/2})\} \gamma'(\beta_{-1}^0)(\widehat{\beta}_{-1} - \beta_{-1}^0), \end{aligned}$$

where

$$\begin{aligned}\gamma'(\boldsymbol{\beta}_{-1}^0) &= \frac{\phi_2(\boldsymbol{\beta}_{-1}^0)\phi(\boldsymbol{\beta}_{-1}^0) - \phi_1(\boldsymbol{\beta}_{-1}^0)\phi_1^T(\boldsymbol{\beta}_{-1}^0)}{\phi(\boldsymbol{\beta}_{-1}^0)^2}, \\ \phi_2(\boldsymbol{\beta}_{-1}) &= E\{\mathbf{X}_{ij,-1}\mathbf{X}_{ij,-1}^T \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1})\}\end{aligned}\quad (\text{S3.113})$$

Therefore, by equation (S3.112),

$$\begin{aligned}& 2\Delta/\phi(\boldsymbol{\beta}_{-1}^0) + \gamma(\boldsymbol{\beta}_{-1}^0)\bar{S}_{U,\xi_u} + \gamma(\boldsymbol{\beta}_{-1}^0)\bar{S}_{V,\xi_v} \\ &= [\gamma(\boldsymbol{\beta}_{-1}^0) + \{1 + O_p(m^{-1/2} + n^{-1/2})\}\gamma'(\boldsymbol{\beta}_{-1}^0)(\hat{\underline{\boldsymbol{\beta}}}_{-1} - \boldsymbol{\beta}_{-1}^0)](\bar{S}_{U,\eta_u,\zeta_u} + \bar{S}_{V,\eta_v,\zeta_v}),\end{aligned}$$

where

$$\begin{aligned}\bar{S}_{U,\xi_u} &= \frac{1}{m} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i + \xi_{u_i}), \\ \bar{S}_{U,\eta_u,\zeta_u} &= \frac{1}{m} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i + \eta_{u_i} + \zeta_{u_i}), \\ \bar{S}_{V,\xi_v} &= \frac{1}{n} \sum_{j=1}^n \exp(\beta_1^{c0} + V_j + \xi_{v_j}), \\ \bar{S}_{V,\eta_v,\zeta_v} &= \frac{1}{n} \sum_{j=1}^n \exp(\beta_1^{c0} + V_j + \eta_{v_j} + \zeta_{v_j}).\end{aligned}$$

And further, we have

$$\begin{aligned}& \gamma'(\beta_1^0)(\hat{\underline{\boldsymbol{\beta}}}_{-1} - \boldsymbol{\beta}_{-1}^0)(\bar{S}_{U,\eta_u,\zeta_u} + \bar{S}_{V,\eta_v,\zeta_v}) \\ &= \frac{2\Delta}{\phi(\boldsymbol{\beta}_{-1}^0)} + \gamma(\boldsymbol{\beta}_{-1}^0)\{(\bar{S}_{U,\xi_u} - \bar{S}_{U,\eta_u,\zeta_u}) + (\bar{S}_{V,\xi_v} - \bar{S}_{V,\eta_v,\zeta_v})\} \\ &+ O_p\{(m^{-1/2} + n^{-1/2})(\hat{\underline{\boldsymbol{\beta}}}_{-1} - \boldsymbol{\beta}_{-1}^0)\}.\end{aligned}\quad (\text{S3.114})$$

Taking logarithms of both sides of (S3.110) and adding over  $i$  from 1 to  $m$ , then dividing by  $m$  we have

$$\begin{aligned} & \log\{\phi(\widehat{\underline{\beta}}_{-1})/\phi(\underline{\beta}_{-1}^0)\} \\ &= \beta_1^{r0} - \widehat{\underline{\beta}}_{-1}^r + \frac{1}{m} \sum_{i=1}^m \left( U_i + \zeta_{u_i} - \widehat{\underline{\mu}}_{u_i} - \frac{1}{2} \widehat{\underline{\lambda}}_{u_i} \right), \end{aligned} \quad (\text{S3.115})$$

which implies that

$$\begin{aligned} & \widehat{\underline{\beta}}_{-1}^r - \beta_1^{r0} \\ &= -\gamma^T(\underline{\beta}_{-1}^0)(\widehat{\underline{\beta}}_{-1} - \underline{\beta}_{-1}^0) \\ & \quad + \frac{1}{m} \sum_{i=1}^m \left( U_i + \zeta_{u_i} - \widehat{\underline{\mu}}_{u_i} - \frac{1}{2} \widehat{\underline{\lambda}}_{u_i} \right) + O_p\{\|\widehat{\underline{\beta}}_{-1} - \underline{\beta}_{-1}^0\|^2\}. \end{aligned} \quad (\text{S3.116})$$

Taking logarithms of both sides of (S3.111) and adding over  $j$  from 1 to  $n$ , then dividing by  $n$  we have

$$\log\{\phi(\widehat{\underline{\beta}}_{-1})/\phi(\underline{\beta}_{-1}^0)\} = \beta_1^{c0} - \widehat{\underline{\beta}}_{-1}^c + \frac{1}{n} \sum_{j=1}^n \left( V_j + \zeta_{v_j} - \widehat{\underline{\mu}}_{v_j} - \frac{1}{2} \widehat{\underline{\lambda}}_{v_j} \right),$$

which implies that

$$\begin{aligned} \widehat{\underline{\beta}}_{-1}^c - \beta_1^{c0} &= -\gamma^T(\underline{\beta}_{-1}^0)(\widehat{\underline{\beta}}_{-1} - \underline{\beta}_{-1}^0) \\ & \quad + \frac{1}{n} \sum_{j=1}^n \left( V_j + \zeta_{v_j} - \widehat{\underline{\mu}}_{v_j} - \frac{1}{2} \widehat{\underline{\lambda}}_{v_j} \right) + O_p\{\|\widehat{\underline{\beta}}_{-1} - \underline{\beta}_{-1}^0\|^2\}. \end{aligned}$$

### S3.3 Approximate formulae for $U_i, \hat{\lambda}_{u_i}, V_j$ and $\hat{\lambda}_{v_j}$

Note that (S2.8) implies that

$$\begin{aligned} & \{1 + O_p(n^{\epsilon-1/2})\} \phi(\beta_1^0) \exp(\beta_0^{r0} + U_i) \\ = & \{1 + O_p(n^{\epsilon-1/2})\} \phi(\beta_1) \exp\left(\beta_0^r + \hat{\mu}_{u_i} + \frac{1}{2}\hat{\lambda}_{u_i}\right) + \frac{\hat{\mu}_{u_i}}{n\hat{\sigma}_u^2}, \end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Based on (S2.93) and (S2.94), we

have

$$\begin{aligned} & \{1 + O_p(n^{\epsilon-1/2})\} \phi(\beta_{-1}^0) \exp(\beta_1^{r0} + U_i) \tag{S3.117} \\ = & \{1 + O_p(n^{\epsilon-1/2})\} \phi(\beta_{-1}^0) \exp\left(\beta_1^{r0} + \hat{\mu}_{u_i} + \frac{1}{2}\hat{\lambda}_{u_i}\right) + \frac{\hat{\mu}_{u_i}}{n\hat{\sigma}_u^2}, \end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Since  $\max_{1 \leq i \leq m} |U_i| = O_p\{(\log m)^{1/2}\}$ ,

and (S2.22) implies that  $0 < \hat{\lambda}_{u_i} < \hat{\sigma}_u^2$ , we have  $\max_{1 \leq i \leq m} |\hat{\mu}_{u_i}| = O_p\{(\log m)^{1/2}\}$ .

Therefore, by (S3.117),

$$\{1 + O_p(n^{\epsilon-1/2})\} \exp(U_i) = \{1 + O_p(n^{\epsilon-1/2})\} \exp\left(\hat{\mu}_{u_i} + \frac{1}{2}\hat{\lambda}_{u_i}\right) \tag{S3.118}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ , taking logarithms, we have

$$U_i = \hat{\mu}_{u_i} + \frac{1}{2}\hat{\lambda}_{u_i} + O_p(n^{\epsilon-1/2}), \tag{S3.119}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Combining (S2.9), (S2.93), and

(S2.94) we have

$$(n\hat{\lambda}_{u_i})^{-1} = \{1 + O_p(n^{\epsilon-1/2})\} \phi(\beta_{-1}^0) \exp\left(\hat{\mu}_{u_i} + \frac{1}{2}\hat{\lambda}_{u_i} + \beta_1^{r0}\right) + (n\hat{\sigma}_u^2)^{-1},$$

uniformly in  $1 \leq i \leq m$ , for  $\epsilon > 0$ . By (S3.118), we have

$$(n\widehat{\lambda}_{u_i})^{-1} = \{1 + O_p(n^{\epsilon-1/2})\}\phi(\boldsymbol{\beta}_{-1}^0) \exp(U_i + \beta_1^{r0}) + (n\widehat{\sigma}_u^2)^{-1},$$

uniformly in  $1 \leq i \leq m$ , for  $\epsilon > 0$ . Hence,

$$\widehat{\lambda}_{u_i} = \{n\phi(\boldsymbol{\beta}_{-1}^0) \exp(U_i + \beta_1^{r0})\}^{-1} + O_p(n^{\epsilon-3/2}), \quad (\text{S3.120})$$

uniformly in  $1 \leq i \leq m$ , for  $\epsilon > 0$ . Based on (S2.9), (S2.93), and (S2.95),

we can derive the formulae for  $V_j$  and  $\widehat{\lambda}_{v_j}$  analogously,

$$\begin{aligned} V_j &= \widehat{\mu}_{v_j} + \frac{1}{2}\widehat{\lambda}_{v_j} + O_p(m^{\epsilon-1/2}), \\ \widehat{\lambda}_{v_j} &= \{m\phi(\boldsymbol{\beta}_{-1}^0) \exp(V_j + \beta_1^{c0})\}^{-1} + O_p(m^{\epsilon-3/2}), \end{aligned}$$

uniformly in  $1 \leq j \leq n$ , for  $\epsilon > 0$ .

### S3.4 Approximations to $\zeta_{u_i}$ and $\zeta_{v_j}$

Define the random variable  $\delta_{u_i}$  from (S3.119) by

$$\widehat{\mu}_{u_i} = U_i - \frac{1}{2}\widehat{\lambda}_{u_i} + \delta_{u_i}. \quad (\text{S3.121})$$

Denote  $B_{u_i,k}^0 = \sum_{j=1}^n \mathbf{X}_{ij,-1}^k \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + V_j)$ ,  $B_{u_i,k}^r = \sum_{j=1}^n \mathbf{X}_{ij,-1}^k \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^r)$   
 $B_{u_i,k}^{r0} = \sum_{j=1}^n \mathbf{X}_{ij,-1}^k \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0})$  for  $k = 0, 1$ , and  $\Delta_{u_i} = \sum_{j=1}^n Y_{ij} - B_{u_i,0}^0 \exp(U_i)$  with zero mean and variance  $n\phi(\boldsymbol{\beta}_{-1}^0) \exp\{\beta_1^0 + (\sigma_u^2)^0/2 +$

$(\sigma_v^2)^0/2\}$ . We can write (S2.8) as

$$\begin{aligned} & \sum_{j=1}^n Y_{ij} - \sum_{j=1}^n \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i} + \lambda_{u_i}/2) - \frac{\hat{\mu}_{u_i}}{\hat{\sigma}_u^2} \\ &= \Delta_{u_i} + B_{u_i,0}^0 \exp(U_i) - B_{u_i,0}^r \exp(U_i + \delta_{u_i}) - \frac{\hat{\mu}_{u_i}}{\hat{\sigma}_u^2}, \end{aligned} \quad (\text{S3.122})$$

uniformly in  $1 \leq i \leq m$ . By Taylor expansion of  $\exp(U_i + \delta_{u_i})$ , we have

$$\exp(U_i + \delta_{u_i}) = \exp(U_i) \left\{ 1 + \delta_{u_i} + \frac{1}{2} \delta_{u_i}^2 + O_p(n^{\epsilon-3/2}) \right\},$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . By Taylor expression of  $B_{u_i,0}^r =$

$\sum_{j=1}^n \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^r)$ , we have

$$B_{u_i,0}^r = B_{u_i,0}^{r0} + \chi_{u_i} + O_p\{(m^{-1/2} + n^{-1/2})^3 n^{\epsilon+1}\},$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ , where

$$\begin{aligned} \chi_{u_i} &= \left\{ \widehat{\underline{\beta}}_1^r - \beta_1^{r0} + \frac{1}{2} (\widehat{\underline{\beta}}_1^r - \beta_1^{r0})^2 \right\} B_{u_i,0}^{r0} \\ &\quad + \{ \widehat{\underline{\beta}}_{-1} - \beta_{-1}^0 + (\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0) (\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0) \}^T B_{u_i,1}^{r0} \\ &\quad + \frac{1}{2} (\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0)^T B_{u_i,2}^{r0} (\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0), \end{aligned}$$

where

$$B_{u_i,2}^{r0} = \sum_{j=1}^n \mathbf{X}_{ij,-1} \mathbf{X}_{ij,-1}^T \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0}). \quad (\text{S3.123})$$

Therefore, (S3.122) implies that

$$\begin{aligned}
 & \sum_{j=1}^n Y_{ij} - B_{u_i,0}^r \exp(U_i + \delta_{u_i}) - \frac{\hat{\mu}_{u_i}}{\hat{\sigma}_u^2} \\
 = & \Delta_{u_i} + (B_{u_i,0}^0 - B_{u_i,0}^{r0}) \exp(U_i) - B_{u_i,0}^{r0} \exp(U_i) \left\{ \delta_{u_i} + \frac{1}{2} \delta_{u_i}^2 + O_p(n^{\epsilon-3/2}) \right\} \\
 & - \chi_{u_i} \exp(U_i) \left\{ 1 + \delta_{u_i} + \frac{1}{2} \delta_{u_i}^2 + O_p(n^{\epsilon-3/2}) \right\} - (U_i - \frac{1}{2} \hat{\lambda}_{u_i} + \delta_{u_i}) / \hat{\sigma}_u^2 \\
 & + O_p\{(m^{-1/2} + n^{-1/2})^3 n^{\epsilon+1}\},
 \end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ , and further

$$\begin{aligned}
 & \delta_{u_i} + \frac{1}{2} \delta_{u_i}^2 \frac{(B_{u_i,0}^{r0} + \chi_{u_i}) \exp(U_i)}{(B_{u_i,0}^{r0} + \chi_{u_i}) \exp(U_i) + 1/\hat{\sigma}_u^2} \\
 = & \frac{\Delta_{u_i} + (B_{u_i,0}^0 - B_{u_i,0}^{r0}) \exp(U_i) - \chi_{u_i} \exp(U_i) - (U_i - \hat{\lambda}_{u_i}/2) / \hat{\sigma}_u^2}{(B_{u_i,0}^{r0} + \chi_{u_i}) \exp(U_i) + 1/\hat{\sigma}_u^2} \\
 & + O_p(n^{\epsilon-3/2}) + O_p\{(m^{-1} + n^{-1})^3 n^\epsilon\},
 \end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ , which implies that

$$\begin{aligned}
 \delta_{u_i} &= \frac{\Delta_{u_i} + (B_{u_i,0}^0 - B_{u_i,0}^{r0}) \exp(U_i) - \chi_{u_i} \exp(U_i)}{(B_{u_i,0}^{r0} + \chi_{u_i}) \exp(U_i)} \quad (\text{S3.124}) \\
 &+ O_p(n^{\epsilon-1}) + O_p\{(m^{-1/2} + n^{-1/2})^3 n^\epsilon\} \\
 &= \{n \exp(\beta_1^{r0}) \phi(\beta_{-1}^0)\}^{-1} \Delta_{u_i} \exp(-U_i) \\
 &+ \{n \exp(\beta_1^{r0}) \phi(\beta_{-1}^0)\}^{-1} (B_{u_i,0}^0 - B_{u_i,0}^{r0}) \\
 &- (\hat{\beta}_1^r - \beta_1^{r0}) - \gamma^T(\beta_{-1}^0) (\hat{\beta}_{-1} - \beta_{-1}^0) + O_p(n^{\epsilon-1}) \\
 &+ O_p\{(m^{-1/2} + n^{-1/2})^3 n^\epsilon\}.
 \end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Hence, combining (S3.116), (S3.120), (S3.121), and (S3.124) we have

$$\begin{aligned}
\widehat{\underline{\mu}}_{u_i} &= U_i - \bar{U} + \bar{\zeta}_{u_i} + \{n \exp(\beta_1^{r0}) \phi(\boldsymbol{\beta}_{-1}^0)\}^{-1} (B_{u_i,0}^0 - B_{u_i,0}^{r0}) \\
&\quad + \{n \exp(\beta_1^{r0}) \phi(\boldsymbol{\beta}_{-1}^0)\}^{-1} \Delta_{u_i} \exp(-U_i) + O_p(n^{\epsilon-1}) \\
&\quad + O_p\{(m^{-1/2} + n^{-1/2})^3 n^\epsilon\} \\
&= U_i - \bar{U} + \{n \exp(\beta_1^{r0}) \phi(\boldsymbol{\beta}_{-1}^0)\}^{-1} (B_{u_i,0}^0 - B_{u_i,0}^{r0}) \\
&\quad + \{n \exp(\beta_1^{r0}) \phi(\boldsymbol{\beta}_{-1}^0)\}^{-1} \Delta_{u_i} \exp(-U_i) \\
&\quad + O_p(n^{\epsilon-1}) + O_p\{(m^{-1/2} + n^{-1/2})^3 n^\epsilon\}, \tag{S3.125}
\end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ , where the second equality uses the property  $\bar{\zeta}_{u_i} = O_p(n^{\epsilon-1})$  from the definition of  $\zeta_{u_i}$ .

To derive the expansion of  $\zeta_{u_i}$ , we substitute (S3.120) and (S3.125) into (S3.104),

$$\begin{aligned}
&\exp\left(\widehat{\underline{\mu}}_{u_i} + \frac{1}{2}\widehat{\underline{\lambda}}_{u_i} - U_i\right) \frac{1}{n} \sum_{j=1}^n \left\{ \exp(\mathbf{X}_{ij}^T \widehat{\underline{\beta}}^r) + \exp(\widehat{\underline{\beta}}_1^r) \phi(\widehat{\underline{\beta}}_{-1}^r) \right\} \\
&= \frac{1}{n} \sum_{j=1}^n \left\{ Y_{ij} \exp(-U_i) - \exp(\beta_1^{r0}) \phi(\boldsymbol{\beta}_{-1}^0) \right\} + \exp(\beta_1^{r0}) \phi(\boldsymbol{\beta}_{-1}^0) \{1 - \exp(\zeta_{u_i})\} \\
&\quad - \exp(-U_i) \frac{U_i}{n \widehat{\underline{\sigma}}_u^2} + O_p(n^{\epsilon-3/2}),
\end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ , where

$$\begin{aligned}
& \exp\left(\widehat{\underline{\mu}}_{u_i} + \frac{1}{2}\widehat{\underline{\lambda}}_{u_i} - U_i\right) \\
= & 1 + \{n \exp(\beta_1^{r0})\phi(\underline{\beta}_{-1}^0)\}^{-1}(B_{u_i,0}^0 - B_{u_i,0}^{r0}) \\
& + \{n \exp(\beta_1^{r0})\phi(\underline{\beta}_{-1}^0)\}^{-1}\Delta_{u_i} \exp(-U_i) - \bar{U} \\
& + O_p(n^{\epsilon-1}) + O_p\{(m^{-1/2} + n^{-1/2})^3 n^\epsilon\},
\end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ , therefore, we have

$$\begin{aligned}
& [1 + \{n \exp(\beta_1^{r0})\phi(\underline{\beta}_{-1}^0)\}^{-1}(B_{u_i,0}^0 - B_{u_i,0}^{r0}) \\
& + \{n \exp(\beta_1^{r0})\phi(\underline{\beta}_{-1}^0)\}^{-1}\Delta_{u_i} \exp(-U_i) - \bar{U}] \\
& \times \frac{1}{n} \sum_{j=1}^n \left\{ \exp(\mathbf{X}_{ij}^T \widehat{\underline{\beta}}^r) - \exp(\widehat{\underline{\beta}}_1^r)\phi(\widehat{\underline{\beta}}_{-1}^r) \right\} \\
= & \frac{1}{n} \sum_{j=1}^n \left\{ Y_{ij} \exp(-U_i) - \exp(\beta_1^{r0})\phi(\underline{\beta}_{-1}^0) \right\} \\
& - \exp(\beta_1^{r0})\phi(\underline{\beta}_{-1}^0) \left( \zeta_{u_i} + \frac{1}{2}\zeta_{u_i}^2 \right) \\
& - \exp(-U_i) \frac{U_i}{n\widehat{\underline{\sigma}}_{u_i}^2} + O_p(n^{\epsilon-3/2}),
\end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Further we have

$$\begin{aligned}
& \exp(\beta_1^{r0})\phi(\boldsymbol{\beta}_{-1}^0) \left( \zeta_{u_i} + \frac{1}{2}\zeta_{u_i}^2 \right) \\
= & -[1 + \{n \exp(\beta_1^{r0})\phi(\boldsymbol{\beta}_{-1}^0)\}^{-1}(B_{u_i,0}^0 - B_{u_i,0}^{r0}) \\
& + \{n \exp(\beta_1^{r0})\phi(\boldsymbol{\beta}_{-1}^0)\}^{-1}\Delta_{u_i} \exp(-U_i) - \bar{U}] \\
& \times \frac{1}{n} \sum_{j=1}^n \left\{ \exp(\mathbf{X}_{ij}^T \widehat{\boldsymbol{\beta}}^r) - \exp(\widehat{\beta}_1^r)\phi(\widehat{\boldsymbol{\beta}}_{-1}) \right\} \\
& + \frac{1}{n} \sum_{j=1}^n \left\{ Y_{ij} \exp(-U_i) - \exp(\beta_1^{r0})\phi(\boldsymbol{\beta}_{-1}^0) \right\} - \exp(-U_i) \frac{U_i}{n\widehat{\sigma}_u^2} + O_p(n^{\epsilon-3/2}),
\end{aligned} \tag{S3.126}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Define

$$\begin{aligned}
D_k(b_1, \mathbf{b}_{-1}) &= \frac{1}{n} \sum_{j=1}^n \left\{ \mathbf{X}_{ij}^k \exp(\mathbf{X}_{ij}^T \mathbf{b}) - \exp(b_1)\phi_k(\mathbf{b}_{-1}) \right\} \\
&= O_p(n^{\epsilon-1/2}), k = 0, 1,
\end{aligned} \tag{S3.127}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Using the Taylor expression to

$\exp(\mathbf{X}_{ij}^T \widehat{\boldsymbol{\beta}}^r) - \exp(\widehat{\beta}_1^r)\phi(\widehat{\boldsymbol{\beta}}_{-1})$ , we deduce that

$$\begin{aligned}
& \sum_{j=1}^n \left\{ \exp(\mathbf{X}_{ij}^T \widehat{\boldsymbol{\beta}}^r) - \exp(\widehat{\beta}_1^r)\phi(\widehat{\boldsymbol{\beta}}_{-1}) \right\} \\
= & n \{ D_{u_i,0}(\boldsymbol{\beta}^{r0}) + (\widehat{\beta}_1^r - \beta_1^{r0}) D_{u_i,0}(\boldsymbol{\beta}^{r0}) + (\widehat{\beta}_1 - \beta_1^0) D_{u_i,1}(\boldsymbol{\beta}^{r0}) \} \\
& + O_p\{(m^{-1/2} + n^{-1/2})^2 n^{\epsilon+1/2}\},
\end{aligned} \tag{S3.128}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Substituting (S3.127) and (S3.128)

to (S3.126), and notice that,

$$\begin{aligned} & \sum_{j=1}^n \{Y_{ij} \exp(-U_i) - \exp(\beta_1^{r0}) \phi(\beta_{-1}^0)\} \\ = & \Delta_{u_i} \exp(-U_i) + \sum_{j=1}^n \{\exp(\mathbf{X}_{ij}^T \boldsymbol{\beta} + V_j) - \exp(\beta_1^{r0}) \phi(\beta_{-1}^0)\}, \end{aligned}$$

we have

$$\begin{aligned} & \exp(\beta_1^{r0}) \phi(\beta_{-1}^0) \left( \zeta_{u_i} + \frac{1}{2} \zeta_{u_i}^2 \right) \\ = & \frac{1}{n} (B_{u_i,0}^0 - B_{u_i,0}^{r0}) \\ & + \frac{1}{n} \exp(-U_i) [\Delta_{u_i} \{1 - \exp(-\beta_1^{r0}) \phi(\beta_{-1}^0)^{-1} D_0(\boldsymbol{\beta}^{r0})\} - U_i / \widehat{\sigma}_u^2] \\ & - (\widehat{\beta}_1^r - \beta_1^{r0}) D_0(\boldsymbol{\beta}^{r0}) - D_1(\boldsymbol{\beta}^{r0}) (\widehat{\beta}_{-1} - \beta_{-1}^0)^T - \bar{U} D_0(\boldsymbol{\beta}^{r0}) \\ & + O_p\{(m^{-1/2} + n^{-1/2})^2 n^{\epsilon-1/2}\}, \end{aligned} \tag{S3.129}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ , and therefore,

$$\begin{aligned} & \exp(\beta_1^{r0}) \phi(\beta_{-1}^0) \zeta_{u_i} \\ = & \frac{1}{n} (B_{u_i,0}^0 - B_{u_i,0}^{r0}) \\ & + \frac{1}{n} \exp(-U_i) [\Delta_{u_i} \{1 - \exp(-\beta_1^{r0}) \phi(\beta_{-1}^0)^{-1} D_0(\boldsymbol{\beta}^{r0})\} - U_i / \widehat{\sigma}_u^2] \\ & - (\widehat{\beta}_1^r - \beta_1^{r0}) D_0(\boldsymbol{\beta}^{r0}) - (\widehat{\beta}_1 - \beta_1^0) D_1(\boldsymbol{\beta}^{r0}) - \bar{U} D_0(\boldsymbol{\beta}^{r0}) \\ & - \frac{1}{2n^2} \exp(-\beta_1^{r0}) \phi^{-1}(\beta_{-1}^0) (B_{u_i,0}^0 - B_{u_i,0}^{r0})^2 \\ & - \frac{1}{n^2} \exp(-\beta_1^{r0}) \phi^{-1}(\beta_{-1}^0) (B_{u_i,0}^0 - B_{u_i,0}^{r0}) \exp(-U_i) \Delta_{u_i} \\ & - \frac{1}{2n^2} \exp(-\beta_1^{r0}) \phi^{-1}(\beta_{-1}^0) \exp(-2U_i) \Delta_{u_i}^2 + O_p(n^{\epsilon-3/2}) \\ & + O_p\{(m^{-1/2} + n^{-1/2})^2 n^{\epsilon-1/2}\}, \end{aligned} \tag{S3.130}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Equation (S3.130) implies that

$$\begin{aligned}
& \exp(\beta_1^{r0})\phi(\beta_{-1}^0)\frac{1}{m}\sum_{i=1}^m U_i\zeta_{u_i} \\
= & \frac{1}{mn}\sum_{i=1}^m U_i(B_{u_i,0}^0 - B_{u_i,0}^{r0}) + \frac{1}{mn}\sum_{i=1}^m U_i \exp(-U_i)\Delta_{u_i} \\
& - \frac{1}{mn} \frac{1}{(\sigma_u^2)^0} \sum_{i=1}^m U_i^2 \exp(-U_i) - \frac{\exp(-\beta_1^{r0})\phi^{-1}(\beta_{-1}^0)}{2mn^2} \sum_{i=1}^m U_i (B_{u_i,0}^0 - B_{u_i,0}^{r0})^2 \\
& - \frac{\exp(-\beta_1^{r0})\phi^{-1}(\beta_{-1}^0)}{mn^2} \sum_{i=1}^m U_i (B_{u_i,0}^0 - B_{u_i,0}^{r0}) \exp(-U_i)\Delta_{u_i} \\
& - \frac{\exp(-\beta_1^{r0})\phi^{-1}(\beta_{-1}^0)}{2mn^2} \sum_{i=1}^m U_i \exp(-2U_i)\Delta_{u_i}^2 \\
& + O_p(m^{-1/2}n^{\epsilon-1}) + O_p\{(m^{-1/2} + n^{-1/2})m^{-1/2}n^{\epsilon-1/2}\}. \tag{S3.131}
\end{aligned}$$

for each  $\epsilon > 0$ . Since

$$\begin{aligned}
& E \left[ \sum_{i=1}^m U_i \{B_{u_i,0}^0 - B_{u_i,0}^{r0}\} \right]^2 \\
= & mn(\sigma_u^2)^0 \phi(2\beta_{-1}^0) \exp\{2\beta_1^0 + (\sigma_v^2)^0\} [\exp\{(\sigma_v^2)^0\} - 1],
\end{aligned}$$

we have

$$\frac{1}{mn} \sum_{i=1}^m U_i (B_{u_i,0}^0 - B_{u_i,0}^{r0}) = O_p\{(mn)^{-1/2}\}. \tag{S3.132}$$

Due to

$$\begin{aligned}
& \text{var} \left\{ \sum_{i=1}^m U_i \exp(-U_i) \Delta_{u_i} \right\} \\
&= \sum_{i=1}^m \sum_{j=1}^n E \{ U_i^2 \exp(-2U_i) \\
&\quad \times E [ \{ Y_{ij} - \exp(\mathbf{X}_{ij}^\top \boldsymbol{\beta}^0 + U_i + V_j) \}^2 | \mathbf{X}_{ij}, U_i, V_j ] \} \\
&= mn \phi(\boldsymbol{\beta}_{-1}^0) (\sigma_u^2)^0 \{ 1 + (\sigma_u^2)^0 \} \exp \left\{ \beta_1^0 + \frac{1}{2} (\sigma_u^2)^0 + \frac{1}{2} (\sigma_v^2)^0 \right\},
\end{aligned}$$

we have

$$\frac{1}{mn} \sum_{i=1}^m U_i \exp(-U_i) \Delta_{u_i} = O_p \{ (mn)^{-1/2} \}. \quad (\text{S3.133})$$

By (S3.132) and (S3.133), we have

$$\frac{1}{mn^2} \sum_{i=1}^m U_i \{ B_{u_i,0}^0 - B_{u_i,0}^{r0} \}^2 = O_p(m^{-1/2} n^{\epsilon-1}) \quad (\text{S3.134})$$

$$\frac{1}{mn^2} \sum_{i=1}^m U_i \{ B_{u_i,0}^0 - B_{u_i,0}^{r0} \} \exp(-U_i) \Delta_{u_i} = O_p(m^{-1/2} n^{\epsilon-1}) \quad (\text{S3.135})$$

for each  $\epsilon > 0$ . Together with (S3.131), (S3.132), (S3.133), (S3.134),

(S3.135), and the following facts

$$\begin{aligned}
E \{ U_i^2 \exp(-U_i) \} &= \exp \{ (\sigma_u^2)^0 / 2 \} (\sigma_u^2)^0 \{ 1 + (\sigma_u^2)^0 \}, \\
E \left\{ \sum_{i=1}^m U_i \exp(-2U_i) \Delta_{u_i}^2 \right\} &= -mn (\sigma_u^2)^0 \phi(\boldsymbol{\beta}_{-1}^0) \exp \{ \beta_1^0 + (\sigma_u^2)^0 / 2 + (\sigma_v^2)^0 / 2 \},
\end{aligned}$$

imply that

$$\frac{1}{m} \sum_{i=1}^m U_i \zeta_{u_i} = O_p \{ (mn)^{-1/2} + n^{-1} \}.$$

Using (S3.130) and the following facts

$$\begin{aligned}\frac{1}{mn} \sum_{i=1}^m \exp(-U_i) \Delta_{u_i} &= O_p\{(mn)^{-1/2}\}, \\ \frac{1}{mn} \sum_{i=1}^m \exp(-2U_i) \Delta_{u_i}^2 &= O_p(1),\end{aligned}$$

we obtain the following property,

$$\begin{aligned}\frac{1}{m} \sum_{i=1}^m \zeta_{u_i} &= \frac{1}{mn \phi(\beta_{-1}^0) \exp(\beta_1^{r0})} \sum_{i=1}^m (B_{u_i,0}^0 - B_{u_i,0}^{r0}) \\ &\quad + O_p\{(mn)^{-1/2} + n^{-1}\}.\end{aligned}\tag{S3.136}$$

The following properties can be derived analogously:

$$\begin{aligned}& \exp(\beta_1^{c0}) \phi(\beta_{-1}^0) \zeta_{v_j} \\ = & \frac{1}{m} \{B_{v_j,0}^0 - B_{v_j,0}^{c0}\} \\ & + \frac{1}{m} \exp(-V_j) [\Delta_{v_j} \{1 - \exp(-\beta_1^{c0}) \phi(\beta_{-1}^0)^{-1} D_0(\beta^{c0})\} - V_j / \widehat{\underline{\sigma}}_v^2] \\ & - (\widehat{\underline{\beta}}_{-1}^c - \beta_1^{c0}) D_0(\beta^{c0}) - D_1(\beta^{c0}) (\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0) - \bar{V} D_0(\beta_0^{c0}) \\ & - \frac{1}{2} \exp(-\beta_1^{c0}) \phi^{-1}(\beta_{-1}^0) m^{-2} \{B_{v_j,0}^0 - m \exp(\beta_1^{c0}) \phi(\beta_{-1}^0)\}^2 \\ & - \exp(-\beta_1^{c0}) \phi^{-1}(\beta_{-1}^0) m^{-2} \{B_{v_j,0}^0 - m \exp(\beta_1^{c0}) \phi(\beta_{-1}^0)\} \exp(-V_j) \Delta_{v_j} \\ & - \frac{1}{2} \exp(-\beta_1^{c0}) \phi^{-1}(\beta_{-1}^0) m^{-2} \exp(-2V_j) \Delta_{v_j}^2 \\ & + O_p(m^{\epsilon-3/2}) + O_p\{(m^{-1/2} + n^{-1/2})^2 m^{\epsilon-1/2}\},\end{aligned}$$

uniformly in  $1 \leq j \leq n$ , for each  $\epsilon > 0$ , and

$$\begin{aligned} \frac{1}{n} \sum_{j=1}^n V_j \zeta_{v_j} &= O_p\{(mn)^{-1/2} + m^{-1}\}, \\ \frac{1}{n} \sum_{j=1}^n \zeta_{v_j} &= \{\phi(\boldsymbol{\beta}_{-1}^0) \exp(\beta_1^{c0})\}^{-1} \frac{1}{mn} \sum_{j=1}^n (B_{v_j,0}^0 - B_{v_j,0}^{c0}) \\ &\quad + O_p\{(mn)^{-1/2} + m^{-1}\}. \end{aligned}$$

where  $B_{v_j,0}^0 = \sum_{i=1}^m \exp(\mathbf{X}_{ij}^\top \boldsymbol{\beta}^0 + U_i)$  and  $B_{v_j,0}^{c0} = \sum_{i=1}^m \exp(\mathbf{X}_{ij}^\top \boldsymbol{\beta}^{c0})$ .

### S3.5 Final approximations to $\sigma_u^2 - (\sigma_u^2)^0$ and $\sigma_v^2 - (\sigma_v^2)^0$

Equations (S3.110), (S3.115), and (S3.120) imply that

$$\begin{aligned} \hat{\mu}_{u_i} &= U_i + \zeta_{u_i} - \frac{1}{2} \hat{\lambda}_{u_i} - \log\{\phi(\hat{\boldsymbol{\beta}}_{-1})/\phi(\boldsymbol{\beta}_{-1}^0)\} - (\hat{\beta}_1^r - \beta_1^{r0}) \quad (\text{S3.137}) \\ &= U_i + \zeta_{u_i} - \frac{1}{2} \hat{\lambda}_{u_i} - \gamma(\boldsymbol{\beta}_{-1}^0)(\hat{\boldsymbol{\beta}}_{-1} - \boldsymbol{\beta}_{-1}^0)^\top - (\hat{\beta}_1^r - \beta_1^{r0}) \\ &\quad + O_p\{(\hat{\boldsymbol{\beta}}_{-1} - \boldsymbol{\beta}_{-1}^0)^\top (\hat{\boldsymbol{\beta}}_{-1} - \boldsymbol{\beta}_{-1}^0)\} \\ &= U_i + \zeta_{u_i} - \{2n\phi(\boldsymbol{\beta}_{-1}^0) \exp(U_i + \beta_1^{r0})\}^{-1} - (\bar{U} + \bar{\zeta}_u) \\ &\quad + \left[ 2n\phi(\boldsymbol{\beta}_{-1}^0) \exp\left\{\beta_1^{r0} - \frac{1}{2}(\sigma^2)^0\right\} \right]^{-1} + O_p\{(m^{-1/2} + n^{-1/2})^2\}. \end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Therefore, squaring both sides of

(S3.137) and adding  $i$  from 1 to  $m$ , for  $\epsilon > 0$ ,

$$\begin{aligned} \frac{1}{m} \sum_{i=1}^m \hat{\mu}_{u_i}^2 &= \frac{1}{m} \sum_{i=1}^m (U_i + \zeta_{u_i} - \bar{U} - \bar{\zeta}_u)^2 \\ &\quad - \{mn\phi(\boldsymbol{\beta}_{-1}^0) \exp(\beta_1^{r0})\}^{-1} \sum_{i=1}^m \exp(-U_i)(U_i + \zeta_{u_i} - \bar{U} - \bar{\zeta}_u) \\ &\quad + O_p\{(m^{-1/2} + n^{-1/2})^2\}. \quad (\text{S3.138}) \end{aligned}$$

Combining (S2.12), (S3.115), and (S3.138) we have

$$\begin{aligned}\widehat{\underline{\sigma}}_u^2 &= \frac{1}{m} \sum_{i=1}^m (\widehat{\underline{\lambda}}_{u_i} + \widehat{\underline{\mu}}_{u_i}^2) \\ &= \frac{1}{m} \sum_{i=1}^m (U_i + \zeta_{u_i} - \bar{U} - \bar{\zeta}_u)^2 + O_p\{(m^{-1/2} + n^{-1/2})^2\}\end{aligned}\quad (\text{S3.139})$$

By (S3.136),

$$\begin{aligned}\text{var}(\bar{\zeta}_u) &= \frac{\{\phi(\boldsymbol{\beta}_{-1}^0) \exp(\beta_1^{r0})\}^{-2}}{m^2 n^2} \\ &\quad \times \sum_{i=1}^m \sum_{j=1}^n E\{\exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + V_j) - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0})\}^2 \\ &\quad + \frac{\{\phi(\boldsymbol{\beta}_{-1}^0) \exp(\beta_1^{r0})\}^{-2}}{m^2 n^2} \\ &\quad \times \sum_{i=1}^m \sum_{k \neq i}^m \sum_{j=1}^n E\{\exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + V_j) - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0})\} \\ &\quad \times \{\exp(\mathbf{X}_{kj}^T \boldsymbol{\beta}^0 + V_j) - \exp(\mathbf{X}_{kj}^T \boldsymbol{\beta}^{r0})\} \\ &= \frac{m-1}{mn} [\exp\{(\sigma_v^2)^0\} - 1] + O\{(mn)^{-1}\},\end{aligned}\quad (\text{S3.140})$$

which implies that

$$\bar{\zeta}_u = O_p(n^{-1/2}). \quad (\text{S3.141})$$

Moreover, by (S3.130),

$$\begin{aligned}&\frac{1}{m} \sum_{i=1}^m E \zeta_{u_i}^2 \\ &= \phi^{-2}(\boldsymbol{\beta}_{-1}^0) \exp(-2\beta_1^{r0}) \frac{1}{mn^2} \sum_{i=1}^m E\{B_{u_i,0}^0 - B_{u_i,0}^{r0}\}^2 + O_p(m^{-1/2} n^{-1/2} + n^{-1}) \\ &= O_p(m^{-1/2} n^{-1/2} + n^{-1}).\end{aligned}$$

Combining (S3.139), (S3.140), (S3.141), and (S3.136) we have

$$\begin{aligned}
 & \widehat{\underline{\sigma}}_u^2 - (\sigma_u^2)^0 \\
 &= \frac{1}{m} \sum_{i=1}^m (U_i + \zeta_{u_i} - \bar{U} - \bar{\zeta}_u)^2 - (\sigma_u^2)^0 \\
 &= \frac{1}{m} \sum_{i=1}^m \{U_i^2 - (\sigma_u^2)^0\} + O_p\{(mn)^{-1/2} + m^{-1} + n^{-1}\}. \quad (\text{S3.142})
 \end{aligned}$$

By the assumption  $\log m / \log n \rightarrow \delta$ ,  $\delta \in (1/2, 2)$ , (S3.142) implies the asymptotic normality result of  $\widehat{\underline{\sigma}}_u^2$  in Theorem 2. The expression of  $\widehat{\underline{\sigma}}_v^2$  can be derived analogously:

$$\widehat{\underline{\sigma}}_v^2 = \frac{1}{n} \sum_{j=1}^n (V_j + \zeta_{v_j} - \bar{V} - \bar{\zeta}_v)^2 + O_p\{(m^{-1/2} + n^{-1/2})^2\},$$

and

$$\widehat{\underline{\sigma}}_v^2 - (\sigma_v^2)^0 = \frac{1}{n} \sum_{j=1}^n \{V_j^2 - (\sigma_v^2)^0\} + O_p\{(m^{-1/2} + n^{-1/2})^2\} \quad (\text{S3.143})$$

which implies the asymptotic normality result of  $\widehat{\underline{\sigma}}_v^2$  for the Poisson case in Theorem 2.

### S3.6 Approximations to $\xi_{u_i}$ , $\eta_{u_i}$ , $\xi_{v_j}$ and $\eta_{v_j}$

By (S3.102), we have

$$\begin{aligned}
 & \frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij,-1} \exp\{\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0 + V_j - (\sigma_v^2)^0 / 2\} \\
 &= \phi_1(\boldsymbol{\beta}_{-1}^0) \left\{ 1 + \xi_{u_i} + \frac{1}{2} \xi_{u_i}^2 + O_p(|\xi_{u_i}|^3) \right\},
 \end{aligned}$$

therefore,

$$\begin{aligned}
& \left( \xi_{u_i} + \frac{1}{2} \xi_{u_i}^2 \right) \tag{S3.144} \\
&= \frac{\phi_1(\boldsymbol{\beta}_{-1}^0)^\top}{n \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2} \sum_{j=1}^n \mathbf{X}_{ij,-1} \exp\{\mathbf{X}_{ij,-1}^\top \boldsymbol{\beta}_{-1}^0 + V_j - (\sigma_v^2)^0/2\} - 1 \\
&\quad + O_p(|\xi_{u_i}|^3),
\end{aligned}$$

uniformly in  $1 \leq i \leq m$ . By (S3.130), we can derived that the term

$\max_{1 \leq i \leq m} |\xi_{u_i}| = O_p(n^{\epsilon-1/2})$ . Squaring both sides of (S3.144), we have

$$\begin{aligned}
& \frac{1}{2} \xi_{u_i}^2 \\
&= \frac{1}{2 \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2 \exp\{(\sigma_v^2)^0\}} \\
&\quad \times \left[ \frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij,-1}^\top \phi_1(\boldsymbol{\beta}_{-1}^0) \exp(\mathbf{X}_{ij,-1}^\top \boldsymbol{\beta}_{-1}^0 + V_j) - \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2 \exp\{(\sigma_v^2)^0/2\} \right] \\
&\quad \times \left[ \frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij,-1}^\top \phi_1(\boldsymbol{\beta}_{-1}^0) \exp(\mathbf{X}_{ij,-1}^\top \boldsymbol{\beta}_{-1}^0 + V_j) - \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2 \exp\{(\sigma_v^2)^0/2\} \right] \\
&\quad + O_p(n^{\epsilon-3/2}),
\end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Hence

$$\begin{aligned}
 & \xi_{u_i} \\
 = & \frac{1}{\|\phi_1(\beta_{-1}^0)\|^2 \exp\{(\sigma_v^2)^0/2\}} \\
 & \times \left[ \frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij,-1}^\top \phi_1(\beta_{-1}^0) \exp(\mathbf{X}_{ij,-1}^\top \beta_{-1} + V_j) - \|\phi_1(\beta_{-1}^0)\|^2 \exp\{(\sigma_v^2)^0/2\} \right] \\
 & - \frac{1}{2\|\phi_1(\beta_{-1}^0)\|^2 \exp\{(\sigma_v^2)^0\}} \\
 & \times \left[ \frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij,-1}^\top \phi_1(\beta_{-1}^0) \exp(\mathbf{X}_{ij,-1}^\top \beta_{-1} + V_j) - \|\phi_1(\beta_{-1}^0)\|^2 \exp\{(\sigma_v^2)^0/2\} \right] \\
 & \times \left[ \frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij,-1}^\top \phi_1(\beta_{-1}^0) \exp(\mathbf{X}_{ij,-1}^\top \beta_{-1} + V_j) - \|\phi_1(\beta_{-1}^0)\|^2 \exp\{(\sigma_v^2)^0/2\} \right] \\
 & + O_p(n^{\epsilon-3/2}),
 \end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ .

By (S3.103), we have

$$\frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij,-1}^\top \hat{\beta}_{-1}) = \phi_1(\hat{\beta}_{-1}) \left\{ 1 + \eta_{u_i} + \frac{1}{2} \eta_{u_i}^2 + O_p(|\eta_{u_i}|^3) \right\}.$$

Based on the following fact,

$$\begin{aligned}
 & \frac{1}{n\phi_1(\hat{\beta}_{-1}^0)\phi_1(\beta_{-1}^0)^\top} \sum_{j=1}^n \mathbf{X}_{ij,-1}^\top \phi_1(\beta_{-1}^0) \exp(\mathbf{X}_{ij,-1}^\top \hat{\beta}_{-1}) - 1 \\
 = & \frac{1}{n\|\phi_1(\beta_{-1}^0)\|^2} \sum_{j=1}^n \left[ \mathbf{X}_{ij,-1}^\top \phi_1(\beta_{-1}^0) \exp(\mathbf{X}_{ij,-1}^\top \beta_{-1}^0) \right. \\
 & + \exp(\mathbf{X}_{ij,-1}^\top \beta_{-1}^0) \mathbf{X}_{ij,-1}^\top (\hat{\beta}_{-1} - \beta_{-1}^0) - \phi_1(\beta_{-1}^0)^\top \phi_1(\beta_{-1}^0) \\
 & \left. - \phi_1(\beta_{-1}^0)^\top \phi_1'(\beta_{-1}^0)(\hat{\beta}_{-1} - \beta_{-1}^0) + O_p\{\|\hat{\beta}_{-1} - \beta_{-1}^0\|^2\} \right] \\
 = & D_1(0, \beta_{-1}^0) \phi_1(\beta_{-1}^0)^\top / \|\phi_1(\beta_{-1}^0)\|^2 + O_p\{n^{\epsilon-1/2} \|\hat{\beta}_{-1} - \beta_{-1}^0\|\},
 \end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ , we obtain that

$$\begin{aligned} \eta_{u_i} + \frac{1}{2}\eta_{u_i}^2 &= D_1(0, \boldsymbol{\beta}_{-1}^0)^\top \phi_1(\boldsymbol{\beta}_{-1}^0) / \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2 \\ &\quad + O_p\{n^{\epsilon-1/2} \|\widehat{\boldsymbol{\beta}}_{-1} - \boldsymbol{\beta}_{-1}^0\| + |\eta_{u_i}|^3\}, \end{aligned} \quad (\text{S3.145})$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Squaring both sides of (S3.145), we can deduce that

$$\begin{aligned} \eta_{u_i}^2 &= \{D_1(0, \boldsymbol{\beta}_{-1}^0)^\top \phi_1(\boldsymbol{\beta}_{-1}^0)\}^2 / \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^4 \\ &\quad + O_p\{n^{\epsilon-1} \|\widehat{\boldsymbol{\beta}}_{-1} - \boldsymbol{\beta}_{-1}^0\| + |\eta_{u_i}|^3\}, \end{aligned} \quad (\text{S3.146})$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ . Combining (S3.145) and (S3.146) we have

$$\begin{aligned} \eta_{u_i} &= D_1(0, \boldsymbol{\beta}_{-1}^0)^\top \phi_1(\boldsymbol{\beta}_{-1}^0) / \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2 \\ &\quad - \frac{1}{2} \{D_1(0, \boldsymbol{\beta}_{-1}^0)^\top \phi_1(\boldsymbol{\beta}_{-1}^0)\}^2 / \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^4 \\ &\quad + O_p\{\|\widehat{\boldsymbol{\beta}}_{-1} - \boldsymbol{\beta}_{-1}^0\| n^{\epsilon-1/2} + |\eta_{u_i}|^3\}, \end{aligned} \quad (\text{S3.147})$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ .

For the approximations of  $\xi_{v_j}$  and  $\eta_{v_j}$ , we can derive them analogously,

$$\begin{aligned}
 \xi_{v_j} &= \frac{1}{\|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2 \exp\{(\sigma_u^2)^0/2\}} \\
 &\quad \times \left[ \frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij}^T \phi_1(\boldsymbol{\beta}_{-1}^0) \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0 + V_j) - \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2 \exp\{(\sigma_v^2)^0/2\} \right], \\
 &\quad - \frac{1}{2\|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2 \exp\{(\sigma_u^2)^0\}} \\
 &\quad \times \left[ \frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij,-1}^T \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0 + V_j) - \phi_1(\boldsymbol{\beta}_{-1}^0) \exp\{(\sigma_u^2)^0/2\} \right] \\
 &\quad \times \left[ \frac{1}{n} \sum_{j=1}^n \mathbf{X}_{ij,-1}^T \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0 + V_j) - \phi_1(\boldsymbol{\beta}_{-1}^0) \exp\{(\sigma_u^2)^0/2\} \right] \\
 &\quad + O_p(m^{\epsilon-3/2}), \\
 \eta_{v_j} &= D_1(0, \boldsymbol{\beta}_{-1}^0) \phi_1(\boldsymbol{\beta}_{-1}^0) / \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2 - \frac{1}{2} \{D_1(0, \boldsymbol{\beta}_{-1}^0) \phi_1(\boldsymbol{\beta}_{-1}^0)\}^2 / \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^4 \\
 &\quad + O_p\{(m^{-1/2} + n^{-1/2})m^{\epsilon-1/2}\},
 \end{aligned}$$

uniformly in  $1 \leq j \leq n$ , for each  $\epsilon > 0$ .

### S3.7 Final approximations to $\hat{\underline{\beta}}_1 - \beta_1^0$ and $\hat{\underline{\beta}}_{-1} - \beta_{-1}^0$

For a true value  $\boldsymbol{\beta}_{-1}^0$  and the bounded random variable  $\mathbf{X}_{ij,-1}$ 's, we have

$$\begin{aligned}
 &\text{var} \left\{ \frac{1}{m} \sum_{i=1}^m D_k(0, \boldsymbol{\beta}_{-1}^0) \right\} \\
 &= \frac{1}{n^2 m^2} \sum_{i=1}^m \sum_{j=1}^n E[\{\mathbf{X}_{ij,-1}^k \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0) - \phi_k(\boldsymbol{\beta}_{-1}^0)\}^T \\
 &\quad \times \{\mathbf{X}_{ij,-1}^k \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0) - \phi_k(\boldsymbol{\beta}_{-1}^0)\}] \\
 &= \frac{1}{mn} \text{var}\{\mathbf{X}_{-1}^k \exp(\mathbf{X}_{-1}^T \boldsymbol{\beta}_{-1}^0)\} = O(m^{-1}n^{-1}),
 \end{aligned}$$

furthermore,

$$\frac{1}{m} \sum_{i=1}^m D_k(0, \beta_{-1}^0) = O_p(m^{-1/2} n^{-1/2}). \quad (\text{S3.148})$$

By the equations (S3.130), (S3.147), and (S3.148), we have

$$\begin{aligned} & \frac{1}{m} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i + \eta_{u_i} + \zeta_{u_i}) \\ = & \exp \left\{ \beta_1^{r0} + \frac{1}{2} (\sigma_u^2)^0 \right\} + O_p(n^{-1/2}). \end{aligned} \quad (\text{S3.149})$$

Analogously,

$$\begin{aligned} & \frac{1}{n} \sum_{j=1}^n \exp(\beta_1^{c0} + V_j + \eta_{v_j} + \zeta_{v_j}) \\ = & \exp \left\{ \beta_1^{c0} + \frac{1}{2} (\sigma_v^2)^0 \right\} + O_p(m^{-1/2}). \end{aligned} \quad (\text{S3.150})$$

Combining (S3.130), (S3.144), (S3.147), and (S3.148) we have

$$\begin{aligned} & \bar{S}_{U, \xi_u} - \bar{S}_{U, \eta_u, \zeta_u} \\ = & \frac{1}{m} \sum_{i=1}^m \left\{ \exp(\beta_1^{r0} + U_i + \xi_{u_i}) - \exp(\beta_1^{r0} + U_i + \eta_{u_i} + \zeta_{u_i}) \right\} \\ = & \frac{1}{m} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i) \left( \xi_{u_i} + \frac{1}{2} \xi_{u_i}^2 - \eta_{u_i} - \frac{1}{2} \eta_{u_i}^2 - \zeta_{u_i} - \frac{1}{2} \zeta_{u_i}^2 - \eta_{u_i} \zeta_{u_i} \right) \\ & + O_p \left\{ (m^{-1/2} + n^{-1/2}) m^{-1/2} n^{\epsilon-1/2} + n^{\epsilon-3/2} \right\}, \end{aligned} \quad (\text{S3.151})$$

for each  $\epsilon > 0$ . By (S3.144) and (S3.145), we have

$$\begin{aligned}
 & \xi_{u_i} + \frac{1}{2}\xi_{u_i}^2 - \eta_{u_i} - \frac{1}{2}\eta_{u_i}^2 \\
 = & \frac{\phi_1(\boldsymbol{\beta}_{-1}^0)^T}{\|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2 \exp\{(\sigma_v^2)^0/2\}} \\
 & \times \frac{1}{n} \sum_{j=1}^n [\mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0 + V_j) - \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0) \exp\{(\sigma_v^2)^0/2\}] \\
 & + O_p\{n^{\epsilon-3/2}\}.
 \end{aligned}$$

Furthermore,

$$\begin{aligned}
 & \frac{1}{m} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i) (\xi_{u_i} + \frac{1}{2}\xi_{u_i}^2 - \eta_{u_i} - \frac{1}{2}\eta_{u_i}^2) \\
 = & \frac{1}{mn\|\phi_1(\boldsymbol{\beta}_1^0)\|^2} \sum_{i=1}^m \sum_{j=1}^n \{ \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + U_i + V_j) \\
 & - \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} + U_i) \} \phi_1(\boldsymbol{\beta}_{-1}^0) + O_p(n^{\epsilon-3/2}). \quad (\text{S3.152})
 \end{aligned}$$

By (S3.129), we have

$$\begin{aligned}
 & \frac{1}{m} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i) (\zeta_{u_i} + \frac{1}{2}\zeta_{u_i}^2) \\
 = & \phi^{-1}(\boldsymbol{\beta}_{-1}^0) \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \exp(U_i) \{ \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + V_j) - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0}) \} \\
 & + \phi^{-1}(\boldsymbol{\beta}_{-1}^0) \frac{1}{m} \sum_{i=1}^m \frac{1}{n} [\Delta_{u_i} \{ 1 - \phi^{-1}(\boldsymbol{\beta}_{-1}^0) \exp(-\beta_1^{r0}) D_0(\boldsymbol{\beta}^{r0}) \} - U_i / \hat{\sigma}_u^2] \\
 & - \phi^{-1}(\boldsymbol{\beta}_{-1}^0) \frac{1}{m} \sum_{i=1}^m (\hat{\boldsymbol{\beta}}_{-1} - \boldsymbol{\beta}_{-1}^0) D_1(\boldsymbol{\beta}^{r0}) \exp(\beta_1^{r0} + U_i) \\
 & - \phi^{-1}(\boldsymbol{\beta}_{-1}^0) \frac{1}{m} \sum_{i=1}^m \bar{U} D_0(\boldsymbol{\beta}^{r0}) \exp(\beta_1^{r0} + U_i) \\
 & + O_p\{(m^{-1/2} + n^{-1/2})^2 n^{\epsilon-1/2}\}. \quad (\text{S3.153})
 \end{aligned}$$

By (S3.130) and (S3.147), we can derive that

$$\begin{aligned}
& \frac{1}{m} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i) \eta_{u_i} \zeta_{u_i} = \frac{1}{mn^2 \phi(\boldsymbol{\beta}_{-1}^0) \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i) \\
& \times \sum_{j=1}^n \{ \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0) - \phi_1(\boldsymbol{\beta}_{-1}^0) \}^T \phi_1(\boldsymbol{\beta}_{-1}^0) \\
& \times \sum_{j=1}^n \{ Y_{ij} \exp(-U_i) - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0}) \} + O_p(n^{\epsilon-3/2}).
\end{aligned}$$

Since

$$E \left\{ \frac{1}{m} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i) \eta_{u_i} \zeta_{u_i} \right\} = 0,$$

and

$$\begin{aligned}
& E \left\{ \frac{1}{m} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i) \eta_{u_i} \zeta_{u_i} \right\}^2 = \frac{1}{m^2 n^4 \phi(\boldsymbol{\beta}_{-1}^0)^2 \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^4} \\
& \times E \left( \sum_{i=1}^m \left[ \sum_{j=1}^n \{ \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0) - \phi_1(\boldsymbol{\beta}_{-1}^0) \}^T \phi_1(\boldsymbol{\beta}_{-1}^0) \right. \right. \\
& \times \left. \left. \sum_{j=1}^n \{ Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} + U_i) \} \right]^2 \right) + \frac{1}{m^2 n^4 \phi(\boldsymbol{\beta}_{-1}^0)^2 \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^4} \\
& \times E \left( \sum_{i=1}^m \sum_{k \neq i}^m \left[ \sum_{j=1}^n \{ \mathbf{X}_{ij,-1} \exp(\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0) - \phi_1(\boldsymbol{\beta}_{-1}^0) \}^T \phi_1(\boldsymbol{\beta}_{-1}^0) \right. \right. \\
& \times \sum_{j=1}^n \{ Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} + U_i) \} \left. \right. \\
& \times \left. \left[ \sum_{j=1}^n \{ \mathbf{X}_{kj,-1} \exp(\mathbf{X}_{kj,-1}^T \boldsymbol{\beta}_{-1}^0) - \phi_1(\boldsymbol{\beta}_{-1}^0) \}^T \phi_1(\boldsymbol{\beta}_{-1}^0) \right. \right. \\
& \times \left. \left. \sum_{j=1}^n \{ Y_{kj} - \exp(\mathbf{X}_{kj}^T \boldsymbol{\beta}^{r0} + U_k) \} \right] \right) \\
& = O_p(m^{-1} n^{-2} + n^{-3}),
\end{aligned}$$

we derive that

$$\frac{1}{m} \sum_{i=1}^m \exp(\beta_1^{r0} + U_i) \eta_{u_i} \zeta_{u_i} = O_p(m^{-1/2} n^{-1} + n^{-3/2}). \quad (\text{S3.154})$$

Combining (S3.151), (S3.152), (S3.153), and (S3.154) we have

$$\begin{aligned} & \bar{S}_{U, \xi_u} - \bar{S}_{U, \eta_u, \zeta_u} \\ = & \frac{1}{mn \|\phi_1(\beta_{-1}^0)\|^2} \sum_{i=1}^m \sum_{j=1}^n \{\mathbf{X}_{ij,-1} - \gamma(\beta_{-1}^0)\}^T \phi_1(\beta_{-1}^0) \\ & \times \{\exp(\mathbf{X}_{ij}^T \beta^0 + U_i + V_j) - \exp(\mathbf{X}_{ij}^T \beta^{r0} + U_i)\} \\ & + \frac{1}{mn \|\phi_1(\beta_{-1}^0)\|^2} \sum_{i=1}^m \sum_{j=1}^n \gamma(\beta_{-1}^0)^T \phi_1(\beta_{-1}^0) \\ & \times \{\exp(\mathbf{X}_{ij}^T \beta^0 + U_i + V_j) - \exp(\mathbf{X}_{ij}^T \beta^{r0} + U_i)\} \\ & - \frac{1}{mn \phi(\beta_{-1}^0)} \sum_{i=1}^m \sum_{j=1}^n \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \beta^{r0} + U_i)\} \\ = & \frac{1}{mn \|\phi_1(\beta_{-1}^0)\|^2} \sum_{i=1}^m \sum_{j=1}^n \{\mathbf{X}_{ij,-1} - \gamma(\beta_{-1}^0)\}^T \phi_1(\beta_{-1}^0) \\ & \times \{\exp(\mathbf{X}_{ij}^T \beta^0 + U_i + V_j) - \exp(\mathbf{X}_{ij}^T \beta^{r0} + U_i)\} \\ & - \frac{1}{mn \phi(\beta_{-1}^0)} \sum_{i=1}^m \sum_{j=1}^n \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \beta^0 + U_i + V_j)\} \\ & + O_p(m^{\epsilon-3/2} + n^{\epsilon-3/2}), \end{aligned} \quad (\text{S3.155})$$

for each  $\epsilon > 0$ . We can derive the following property analogously

$$\begin{aligned}
& \bar{S}_{V, \xi_v} - \bar{S}_{V, \eta_v, \zeta_v} \\
= & \frac{1}{mn \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2} \sum_{i=1}^m \sum_{j=1}^n \{\mathbf{X}_{ij, -1} - \gamma(\boldsymbol{\beta}_{-1}^0)\}^T \phi_1(\boldsymbol{\beta}_{-1}^0) \\
& \times \{\exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + U_i + V_j) - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{c0} + V_j)\} \\
& - \frac{1}{mn \|\phi_1(\boldsymbol{\beta}_{-1}^0)\|^2} \sum_{j=1}^n \gamma(\boldsymbol{\beta}_{-1}^0)^T \phi_1(\boldsymbol{\beta}_{-1}^0) \Delta_{v_j} \\
& + O_p(m^{\epsilon-3/2} + n^{\epsilon-3/2}), \tag{S3.156}
\end{aligned}$$

for each  $\epsilon > 0$ , where  $\Delta_{v_j} = \sum_{i=1}^m \{Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + U_i + V_j)\}$ .

Combining with (S3.114), (S3.149), (S3.150), (S3.155), and (S3.156) we

have

$$\begin{aligned}
& \gamma'(\boldsymbol{\beta}_{-1}^0)(\hat{\underline{\boldsymbol{\beta}}}_{-1} - \boldsymbol{\beta}_{-1}^0) 2 \exp(\beta_1^0) \exp\{(\sigma_u^2)^0/2 + (\sigma_v^2)^0/2\} \\
= & T/\phi(\boldsymbol{\beta}_{-1}^0) + O_p\{(m^{-1/2} + n^{-1/2})(\hat{\underline{\boldsymbol{\beta}}}_{-1} - \boldsymbol{\beta}_{-1}^0)\}, \tag{S3.157}
\end{aligned}$$

where

$$\begin{aligned}
T = & \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \{\mathbf{X}_{ij, -1} - \gamma(\boldsymbol{\beta}_{-1}^0)\} \\
& \times \{2Y_{ij} - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} + U_i) - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{c0} + V_j)\}.
\end{aligned}$$

$T$  is asymptotically normally distributed with zero mean and variance

$$\begin{aligned}
 & \text{var}(T) \\
 = & \frac{1}{mn} 4\{\phi_2(\boldsymbol{\beta}_{-1}^0) - \gamma(\boldsymbol{\beta}_{-1}^0)\phi_1(\boldsymbol{\beta}_{-1}^0)^T\} \exp\{\beta_1^0 + (\sigma_u^2)^0/2 + (\sigma_v^2)^0/2\} \\
 & + \frac{1}{mn} \{\phi_2(2\boldsymbol{\beta}_{-1}^0) - 2\gamma(\boldsymbol{\beta}_{-1}^0)\phi_1(2\boldsymbol{\beta}_{-1}^0)^T + \gamma(\boldsymbol{\beta}_{-1}^0)\gamma(\boldsymbol{\beta}_{-1}^0)^T\phi(2\boldsymbol{\beta}_{-1}^0)\} \\
 & \times \exp\{2\beta_1^0 + (\sigma_u^2)^0 + (\sigma_v^2)^0\} \\
 & \times [4\exp\{(\sigma_u^2)^0 + (\sigma_v^2)^0\} - 3\exp\{(\sigma_u^2)^0\} - 3\exp\{(\sigma_v^2)^0\} + 2].
 \end{aligned}$$

Therefore,

$$\sqrt{mn}T \rightarrow N(0, \boldsymbol{\Sigma}), \quad (\text{S3.158})$$

in distribution, as  $n \rightarrow \infty, m \rightarrow \infty$ , where

$$\begin{aligned}
 & \boldsymbol{\Sigma} \\
 = & 4\{\phi_2(\boldsymbol{\beta}_{-1}^0) - \gamma(\boldsymbol{\beta}_{-1}^0)\phi_1(\boldsymbol{\beta}_{-1}^0)^T\} \exp\{\beta_1^0 + (\sigma_u^2)^0/2 + (\sigma_v^2)^0/2\} \\
 & + \{\phi_2(2\boldsymbol{\beta}_{-1}^0) - 2\gamma(\boldsymbol{\beta}_{-1}^0)\phi_1(2\boldsymbol{\beta}_{-1}^0)^T + \gamma(\boldsymbol{\beta}_{-1}^0)\gamma(\boldsymbol{\beta}_{-1}^0)^T\phi(2\boldsymbol{\beta}_{-1}^0)\} \\
 & \times \exp\{2\beta_1^0 + (\sigma_u^2)^0 + (\sigma_v^2)^0\} \\
 & \times [4\exp\{(\sigma_u^2)^0 + (\sigma_v^2)^0\} - 3\exp\{(\sigma_u^2)^0\} - 3\exp\{(\sigma_v^2)^0\} + 2].
 \end{aligned}$$

Combining (S3.157) and (S3.158) we have

$$\hat{\underline{\boldsymbol{\beta}}}_{-1} - \boldsymbol{\beta}_{-1}^0 = (mn)^{-1/2} \mathbf{Z}_3 + O_p(m^{-1}n^{-1/2} + m^{-1/2}n^{-1}),$$

where  $\mathbf{Z}_3$  is a normal distribution with zero mean and variance

$$\begin{aligned}
 & \Sigma_3 \\
 = & \frac{\phi^2(\boldsymbol{\beta}_{-1}^0)}{\exp\{\beta_1^0 + (\sigma_u^2)^0/2 + (\sigma_v^2)^0/2\}} \{\phi_2(\boldsymbol{\beta}_{-1}^0)\phi(\boldsymbol{\beta}_{-1}^0) - \phi_1(\boldsymbol{\beta}_{-1}^0)\phi_1(\boldsymbol{\beta}_{-1}^0)^\top\}^{-1} \\
 & \{\phi_2(\boldsymbol{\beta}_{-1}^0) - \gamma(\boldsymbol{\beta}_{-1}^0)\phi_1(\boldsymbol{\beta}_{-1}^0)^\top\} \{\phi_2(\boldsymbol{\beta}_{-1}^0)\phi(\boldsymbol{\beta}_{-1}^0) - \phi_1(\boldsymbol{\beta}_{-1}^0)\phi_1(\boldsymbol{\beta}_{-1}^0)^\top\}^{-1} \\
 & + \frac{1}{4}\phi^2(\boldsymbol{\beta}_{-1}^0) \{\phi_2(\boldsymbol{\beta}_{-1}^0)\phi(\boldsymbol{\beta}_{-1}^0) - \phi_1(\boldsymbol{\beta}_{-1}^0)\phi_1(\boldsymbol{\beta}_{-1}^0)^\top\}^{-1} \\
 & \times \{\phi_2(2\boldsymbol{\beta}_{-1}^0) - 2\gamma(\boldsymbol{\beta}_{-1}^0)\phi_1(2\boldsymbol{\beta}_{-1}^0)^\top + \gamma(\boldsymbol{\beta}_{-1}^0)\gamma(\boldsymbol{\beta}_{-1}^0)^\top\phi(2\boldsymbol{\beta}_{-1}^0)\} \\
 & \times \{\phi_2(\boldsymbol{\beta}_{-1}^0)\phi(\boldsymbol{\beta}_{-1}^0) - \phi_1(\boldsymbol{\beta}_{-1}^0)\phi_1(\boldsymbol{\beta}_{-1}^0)^\top\}^{-1} \\
 & \times [4 \exp\{(\sigma_u^2)^0 + (\sigma_v^2)^0\} - 3 \exp(\sigma_u^2)^0 - 3 \exp\{(\sigma_v^2)^0\} + 2].
 \end{aligned}$$

By (S3.116), (S3.117), (S3.142), and (S3.143), we have

$$\begin{aligned}
 & \widehat{\underline{\beta}}_1 - \beta_1^0 \\
 = & -\gamma(\beta_1^0)^\top (\widehat{\underline{\beta}}_{-1} - \boldsymbol{\beta}_{-1}^0) + \frac{1}{2m} \sum_{i=1}^m (U_i + \zeta_{u_i}) \\
 & + \frac{1}{2n} \sum_{j=1}^n (V_j + \zeta_{v_j}) - \frac{1}{4} \{\widehat{\underline{\sigma}}_u^2 - (\sigma_u^2)^0 + \widehat{\underline{\sigma}}_v^2 - (\sigma_v^2)^0\} \\
 = & \frac{1}{2} (\bar{U} + \bar{\zeta}_u + \bar{V} + \bar{\zeta}_v) - \frac{1}{4m} \sum_{i=1}^m \{U_i^2 - (\sigma_u^2)^0\} - \frac{1}{4n} \sum_{j=1}^n \{V_j^2 - (\sigma_v^2)^0\} \\
 & + O_p\{(mn)^{-1/2} + m^{-1} + n^{-1}\} \\
 := & S_1 + S_2 + S_3 + S_4 + S_5 + S_6 + O_p\{(m^{-1/2} + n^{-1/2})^2\}, \quad (\text{S3.159})
 \end{aligned}$$

where

$$\begin{aligned}
S_1 &= \frac{1}{2}\bar{\zeta}_u, \\
S_2 &= \frac{1}{2}\bar{\zeta}_v, \\
S_3 &= \frac{1}{2}\bar{U} = \frac{1}{2m} \sum_{i=1}^m U_i, \\
S_4 &= \frac{1}{2}\bar{V} = \frac{1}{2n} \sum_{j=1}^n V_j, \\
S_5 &= -\frac{1}{4m} \sum_{i=1}^m (U_i^2 - (\sigma_u^2)^0), \\
S_6 &= -\frac{1}{4n} \sum_{j=1}^n (V_j^2 - (\sigma_v^2)^0).
\end{aligned}$$

By the requirements of multivariate central limit theorem, we need to check the boundedness of covariances of  $(S_1, S_2, S_3, S_4, S_5, S_6)$ . The diagonal elements can be calculated as follows,

$$\text{var}(S_1) = \frac{1}{4n} [\exp\{(\sigma_v^2)^0\} - 1] + O\{(mn)^{-1}\}, \quad (\text{S3.160})$$

$$\text{var}(S_2) = \frac{1}{4m} [\exp\{(\sigma_u^2)^0\} - 1] + O\{(mn)^{-1}\} \quad (\text{S3.161})$$

$$\text{var}(S_3) = \frac{1}{4m} (\sigma_u^2)^0, \quad (\text{S3.162})$$

$$\text{var}(S_4) = \frac{1}{4n} (\sigma_v^2)^0, \quad (\text{S3.163})$$

$$\text{var}(S_5) = \frac{1}{8m} \{(\sigma_u^2)^0\}^2, \quad (\text{S3.164})$$

$$\text{var}(S_6) = \frac{1}{8n} \{(\sigma_v^2)^0\}^2. \quad (\text{S3.165})$$

The covariances can be computed as follows,

$$\begin{aligned}
& \text{cov}(S_1, S_2) \\
&= \frac{\exp(-\beta_1^{r0} - \beta_1^{c0})}{4m^2n^2\phi(\beta_{-1}^0)^2} \sum_{i=1}^m \sum_{j=1}^n E[\{\exp(\mathbf{X}_{ij}^T \beta^0 + V_j) - \exp(\mathbf{X}_{ij}^T \beta^{r0})\} \\
&\quad \times \{\exp(\mathbf{X}_{ij}^T \beta^0 + U_i) - \exp(\mathbf{X}_{ij}^T \beta^{c0})\}] \\
&\quad + \frac{\exp(-\beta_1^{r0} - \beta_1^{c0})}{4m^2n^2\phi(\beta_{-1}^0)^2} \\
&\quad \times \sum_{i=1}^m \sum_{k \neq i}^m \sum_{j=1}^n E[\{\exp(\mathbf{X}_{ij}^T \beta^0 + V_j) - \exp(\mathbf{X}_{ij}^T \beta^{r0})\} \\
&\quad \times \{\exp(\mathbf{X}_{kj}^T \beta^0 + U_k) - \exp(\mathbf{X}_{ij}^T \beta^{c0})\}] \\
&\quad + \frac{\exp(-\beta_1^{r0} - \beta_1^{c0})}{4m^2n^2\phi(\beta_{-1}^0)^2} \\
&\quad \times \sum_{i=1}^m \sum_{j=1}^n \sum_{l \neq j}^n E[\{\exp(\mathbf{X}_{ij}^T \beta^0 + V_j) - \exp(\mathbf{X}_{ij}^T \beta^{r0})\} \\
&\quad \times \{\exp(\mathbf{X}_{il}^T \beta^0 + U_i) - \exp(\mathbf{X}_{il}^T \beta^{c0})\}] \\
&= O\{(mn)^{-1}\}, \tag{S3.166}
\end{aligned}$$

$$\begin{aligned}
& \text{cov}(S_1, S_4) \\
&= \frac{\exp(-\beta_1^{r0})}{4mn^2\phi(\beta_{-1}^0)} \sum_{i=1}^m \sum_{j=1}^n E[V_j \{\exp(\mathbf{X}_{ij}^T \beta^0 + V_j) - \exp(\mathbf{X}_{ij}^T \beta^{r0})\}] \\
&= \frac{1}{4n} (\sigma_v^2)^0, \tag{S3.167}
\end{aligned}$$

$$\begin{aligned}
& \text{cov}(S_1, S_6) \\
&= -\frac{\exp(-\beta_1^{r0})}{8mn^2\phi(\boldsymbol{\beta}_{-1}^0)} \sum_{i=1}^m \sum_{j=1}^n E[\{\exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + V_j) - \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0})\} \\
&\quad \{V_j^2 - (\sigma_v^2)^0\}] \\
&= -\frac{\exp(\beta_1^0 - \beta_1^{r0})}{8n} E[\{V_j^2 - (\sigma_v^2)^0\} \exp(V_j)] \\
&= -\frac{1}{8n} \{(\sigma_v^2)^0\}^2, \tag{S3.168}
\end{aligned}$$

$$\text{cov}(S_2, S_3) = \frac{1}{4m} (\sigma_u^2)^0, \tag{S3.169}$$

$$\text{cov}(S_2, S_5) = -\frac{1}{8m} \{(\sigma_u^2)^0\}^2, \tag{S3.170}$$

and others are zeros.

For simplicity, combining (S3.160)-(S3.170) we define two matrices by

$$\mathbf{\Gamma}_1 = \frac{1}{8} \begin{pmatrix} 2[\exp\{(\sigma_u^2)^0\} - 1] & 2(\sigma_u^2)^0 & -\{(\sigma_u^2)^0\}^2 \\ 2(\sigma_u^2)^0 & 2(\sigma_u^2)^0 & 0 \\ -\{(\sigma_u^2)^0\}^2 & 0 & \{(\sigma_u^2)^0\}^2 \end{pmatrix} \tag{S3.171}$$

and

$$\mathbf{\Gamma}_2 = \frac{1}{8} \begin{pmatrix} 2[\exp\{(\sigma_v^2)^0\} - 1] & 2(\sigma_v^2)^0 & -\{(\sigma_v^2)^0\}^2 \\ 2(\sigma_v^2)^0 & 2(\sigma_v^2)^0 & 0 \\ -\{(\sigma_v^2)^0\}^2 & 0 & \{(\sigma_v^2)^0\}^2 \end{pmatrix}. \tag{S3.172}$$

Combining (S3.172)-(S3.171) and following the multivariate central limit

theorem we deduce that

$$\begin{aligned} & (\sqrt{m}(S_2, S_3, S_5), \sqrt{n}(S_1, S_4, S_6))^T \\ \rightarrow & N \left( \begin{pmatrix} \mathbf{0}_3 \\ \mathbf{0}_3 \end{pmatrix}, \begin{pmatrix} \mathbf{\Gamma}_1 & 0 \\ 0 & \mathbf{\Gamma}_2 \end{pmatrix} \right), \end{aligned} \quad (\text{S3.173})$$

as  $m, n \rightarrow \infty$ , where  $\mathbf{0}_3 = (0, 0, 0)^T$ . By results (S3.159), (S3.173), and delta method, we obtain

$$\widehat{\underline{\beta}}_1 - \beta_1^0 = m^{-1/2} \mathbf{1}_3^T Z_2 + n^{-1/2} \mathbf{1}_3^T Z_1 + o_p(m^{-1/2} + n^{-1/2}),$$

where  $Z_1$  and  $Z_2$  are normal distributions with mean zeros and variances  $\mathbf{\Gamma}_1$  and  $\mathbf{\Gamma}_2$ , respectively.

## S4 Proof of Theorem 1 for Gamma regression model

The proof for the consistency and rates of convergence for the estimators

$\widehat{\underline{\beta}}_1, \widehat{\underline{\beta}}_{-1}, \widehat{\underline{\sigma}}_u^2$ , and  $\widehat{\underline{\sigma}}_v^2$  involves two main steps:

Step1. Establish the consistency of estimators  $\beta_1^0, \beta_{-1}^0, (\sigma_u^2)^0$ , and  $(\sigma_v^2)^0$  in §S4.1;

Step2. Extend the consistency results to a rate of convergence by controlling the remainder terms in §S4.2.

### S4.1 Consistency

The variational lower bound of the CL for the Gamma regression model with crossed random effects is

$$\begin{aligned}
& \underline{\mathcal{C}}\ell(\boldsymbol{\Psi}^{rc}, \boldsymbol{\xi}) \\
&= \sum_{i=1}^m \sum_{j=1}^n \left[ \alpha Y_{ij} \left\{ -\exp \left( -\mathbf{X}_{ij}^T \boldsymbol{\beta}^r - \mu_{u_i} + \frac{\lambda_{u_i}}{2} \right) \right\} - \alpha (\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i}) \right] \\
&\quad - \frac{m}{2} \log(\sigma_u^2) - \frac{1}{2\sigma_u^2} \sum_{i=1}^m (\mu_{u_i}^2 + \lambda_{u_i}) + \frac{1}{2} \log(\lambda_{u_i}) \\
&\quad + \sum_{j=1}^n \sum_{i=1}^m \left[ \alpha Y_{ij} \left\{ -\exp \left( -\mathbf{X}_{ij}^T \boldsymbol{\beta}^c - \mu_{v_j} + \frac{\lambda_{v_j}}{2} \right) \right\} - \alpha (\mathbf{X}_{ij}^T \boldsymbol{\beta}^c + \mu_{v_j}) \right] \\
&\quad - \frac{n}{2} \log(\sigma_v^2) - \frac{1}{2\sigma_v^2} \sum_{j=1}^n (\mu_{v_j}^2 + \lambda_{v_j}) + \frac{1}{2} \log \lambda_{v_j}.
\end{aligned}$$

To derive the consistency of the estimates, we take derivatives of  $\underline{\mathcal{C}}\ell(\boldsymbol{\Psi}^{rc}, \boldsymbol{\xi})$  with respect to parameters,

$$\begin{aligned}
\frac{\partial \underline{\mathcal{C}}\ell(\boldsymbol{\Psi}^{rc}, \boldsymbol{\xi})}{\partial \beta_1^r} &= \sum_{i=1}^m \sum_{j=1}^n \alpha Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^r - \mu_{u_i} + \lambda_{u_i}/2) \\
&\quad - \alpha mn,
\end{aligned} \tag{S4.174}$$

$$\begin{aligned}
\frac{\partial \underline{\mathcal{C}}\ell(\boldsymbol{\Psi}^{rc}, \boldsymbol{\xi})}{\partial \beta_1^c} &= \sum_{j=1}^n \sum_{i=1}^m \alpha \{ Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^c - \mu_{v_j} + \lambda_{v_j}/2) - 1 \} \\
&\quad - \alpha mn,
\end{aligned} \tag{S4.175}$$

$$\begin{aligned}
 & \frac{\partial \underline{\mathcal{C}}\ell(\Psi^{rc}, \xi)}{\partial \beta_{-1}} \\
 = & \sum_{i=1}^m \sum_{j=1}^n \alpha \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \beta^r - \mu_{u_i} + \lambda_{u_i}/2) - 1\} \mathbf{X}_{ij,-1} \\
 & + \sum_{j=1}^n \sum_{i=1}^m \alpha \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \beta^c - \mu_{v_j} + \lambda_{v_j}/2) - 1\} \mathbf{X}_{ij,-1},
 \end{aligned} \tag{S4.176}$$

$$\frac{\partial \underline{\mathcal{C}}\ell(\Psi^{rc}, \xi)}{\partial \sigma_u^2} = -\frac{m}{2\sigma_u^2} + \frac{1}{2\sigma_u^4} \sum_{i=1}^m (\mu_{u_i}^2 + \lambda_{u_i}), \tag{S4.177}$$

$$\frac{\partial \underline{\mathcal{C}}\ell(\Psi^{rc}, \xi)}{\partial \sigma_v^2} = -\frac{m}{2\sigma_v^2} + \frac{1}{2\sigma_v^4} \sum_{i=1}^m (\mu_{v_j}^2 + \lambda_{v_j}), \tag{S4.178}$$

for each  $\mu_{u_i}$  and  $\lambda_{u_i}$ ,

$$\begin{aligned}
 & \frac{\partial \underline{\mathcal{C}}\ell(\Psi^{rc}, \xi)}{\partial \mu_{u_i}} \\
 = & \sum_{j=1}^n \alpha \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \beta^r - \mu_{u_i} + \lambda_{u_i}/2) - 1\} - \frac{\mu_{u_i}}{\sigma_u^2},
 \end{aligned} \tag{S4.179}$$

$$\begin{aligned}
 & \frac{\partial \underline{\mathcal{C}}\ell(\Psi^{rc}, \xi)}{\partial \lambda_{u_i}} \\
 = & -\frac{1}{2} \sum_{j=1}^n \alpha Y_{ij} \exp(-\mathbf{X}_{ij}^T \beta^r - \mu_{u_i} + \lambda_{u_i}/2) - \frac{1}{2\sigma_u^2} + \frac{1}{2\lambda_{u_i}},
 \end{aligned} \tag{S4.180}$$

for each  $\mu_{v_j}$  and  $\lambda_{v_j}$ ,

$$\frac{\partial \underline{\mathcal{C}}\ell(\Psi^{rc}, \xi)}{\partial \mu_{v_j}} \tag{S4.181}$$

$$\begin{aligned}
 = & \sum_{i=1}^m \alpha \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \beta^c - \mu_{v_j} + \lambda_{v_j}/2) - 1\} - \frac{\mu_{v_j}}{\sigma_v^2}, \\
 & \frac{\partial \underline{\mathcal{C}}\ell(\Psi^{rc}, \xi)}{\partial \lambda_{v_j}}
 \end{aligned} \tag{S4.182}$$

$$= -\frac{1}{2} \sum_{j=1}^n \alpha Y_{ij} \exp(-\mathbf{X}_{ij}^T \beta^c - \mu_{v_j} + \lambda_{v_j}/2) - \frac{1}{2\sigma_v^2} + \frac{1}{2\lambda_{v_j}}.$$

Setting equations (S4.177) and (S4.178) to zeros and solving we have

$$\hat{\sigma}_u^2 = \frac{1}{m} \sum_{i=1}^m (\hat{\mu}_{u_i}^2 + \hat{\lambda}_{u_i}), \quad (\text{S4.183})$$

$$\hat{\sigma}_v^2 = \frac{1}{n} \sum_{j=1}^n (\hat{\mu}_{v_j}^2 + \hat{\lambda}_{v_j}). \quad (\text{S4.184})$$

Setting (S4.174), (S4.175), (S4.179), and (S4.181) to zeros we have

$$\sum_{i=1}^m \sum_{j=1}^n \alpha \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^r - \mu_{u_i} + \lambda_{u_i}/2) - 1\} = 0, \quad (\text{S4.185})$$

$$\sum_{j=1}^n \sum_{i=1}^m \alpha \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^c - \mu_{v_j} + \lambda_{v_j}/2) - 1\} = 0, \quad (\text{S4.186})$$

$$\sum_{j=1}^n \alpha \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^r - \mu_{u_i} + \lambda_{u_i}/2) - 1\} - \frac{\mu_{u_i}}{\sigma_u^2} = 0, \quad (\text{S4.187})$$

$$\sum_{i=1}^m \alpha \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^c - \mu_{v_j} + \lambda_{v_j}/2) - 1\} - \frac{\mu_{v_j}}{\sigma_v^2} = 0. \quad (\text{S4.188})$$

for  $1 \leq j \leq n$ . By (S4.187), we have

$$\sum_{i=1}^m \sum_{j=1}^n \alpha \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^r - \mu_{u_i} + \lambda_{u_i}/2) - 1\} = \sum_{i=1}^m \frac{\mu_{u_i}}{\sigma_u^2}. \quad (\text{S4.189})$$

Combining (S4.189) and (S4.185) we have

$$\sum_{i=1}^m \hat{\mu}_{u_i} = 0. \quad (\text{S4.190})$$

By (S4.188), we have

$$\sum_{i=1}^m \sum_{j=1}^n \alpha \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^c - \mu_{v_j} + \lambda_{v_j}/2) - 1\} = \sum_{j=1}^n \frac{\mu_{v_j}}{\sigma_v^2}. \quad (\text{S4.191})$$

Combining (S4.191) and (S4.186) we have

$$\sum_{j=1}^n \hat{\mu}_{v_j} = 0. \quad (\text{S4.192})$$

Setting equations (S4.180) and (S4.184) to zeros we have  $\hat{\lambda}_{u_i}$  and  $\hat{\lambda}_{v_j}$  satisfy

$$\hat{\lambda}_{u_i} = \left\{ \sigma_u^{-2} + \sum_{j=1}^n \alpha Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^r - \hat{\mu}_{u_i} + \hat{\lambda}_{u_i}/2) \right\}^{-1}, \quad (\text{S4.193})$$

and

$$\hat{\lambda}_{v_j} = \left\{ \sigma_v^{-2} + \sum_{i=1}^m \alpha Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^c - \hat{\mu}_{v_j} + \hat{\lambda}_{v_j}/2) \right\}^{-1},$$

from which it is obvious that  $0 < \hat{\lambda}_{u_i} < \sigma_u^2$  and  $0 < \hat{\lambda}_{v_j} < \sigma_v^2$ .

Since conditional on  $X_{ij}$ ,  $U_i$ , and  $V_j$ ,  $Y_{ij}$ 's are independent Gamma regression with mean  $\exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^0 + U_i + V_j)$ ,  $1 \leq i \leq m, 1 \leq j \leq n$ , we have

$$E\{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta} - U_i - V_j)\} = \exp(\beta_1^0 - \beta_1) \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1}). \quad (\text{S4.194})$$

By (S4.194), the Markov's inequality and  $m/n = O(1)$ , for all  $C_1, C_2$ , and  $\rho \in (0, 1/2)$ , we have

$$P \left[ \max_{1 \leq i \leq m} \left| \frac{1}{n} \sum_{j=1}^n \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta} - U_i - V_j) - \exp(\beta_1^0 - \beta_1) \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})\} \right| > n^{-\rho} \right] = O(n^{-C_2}). \quad (\text{S4.195})$$

Combining (S2.28), (S2.30), and (S4.195), for all  $C_1, C_2 > 0$  and  $\rho \in (1, 1/2)$ , we have

$$P \left\{ \max_{1 \leq i \leq m} \left| \frac{1}{n} \sum_{j=1}^n Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^r - U_i) - \exp \left\{ \beta_1^0 + \frac{1}{2}(\sigma_u^2)^0 - \beta_1^r \right\} \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1}) \right| > n^{-\rho} \right\} = O(n^{-C_2}), \quad (\text{S4.196})$$

which implies

$$P\left\{\left|\frac{1}{mn}\sum_{i=1}^m\sum_{j=1}^n Y_{ij}\exp(-\mathbf{X}_{ij}^T\boldsymbol{\beta}^r - U_i) - \exp\left\{\beta_1^0 + \frac{1}{2}(\sigma_u^2)^0 - \beta_1^r\right\}\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1}^r)\right| > n^{-\rho}\right\} = O(n^{-C_2}),$$

and

$$P\left\{\left|\frac{1}{mn}\sum_{i=1}^m\sum_{j=1}^n \mathbf{X}_{ij}Y_{ij}\exp(-\mathbf{X}_{ij}^T\boldsymbol{\beta}^r - U_i) - \exp\left\{\beta_1^0 + \frac{1}{2}(\sigma_u^2)^0 - \beta_1^r\right\}\phi_1(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1}^r)\right| > n^{-\rho}\right\} = O(n^{-C_2}). \quad (\text{S4.197})$$

Equating equations (S4.179)-(S4.183) to zeros and solving, the estimates  $\hat{\underline{\mu}}_{u_i}$ ,  $\hat{\underline{\lambda}}_{u_i}$ ,  $\hat{\underline{\mu}}_{v_j}$ , and  $\hat{\underline{\lambda}}_{v_j}$ , can be obtained. Then plugging them into the equations, we have

$$\frac{1}{n}\sum_{j=1}^n \alpha\{Y_{ij}\exp(-\mathbf{X}_{ij}^T\boldsymbol{\beta}^r - \hat{\underline{\mu}}_{u_i} + \hat{\underline{\lambda}}_{u_i}/2) - 1\} = \frac{\hat{\underline{\mu}}_{u_i}}{n\sigma_u^2}, \quad (\text{S4.198})$$

and

$$-\frac{1}{n}\sum_{j=1}^n \alpha Y_{ij}\exp(\hat{\underline{\lambda}}_{u_i}/2 - \mathbf{X}_{ij}^T\boldsymbol{\beta}^r - \hat{\underline{\mu}}_{u_i}) = \frac{1}{n}\left(\frac{1}{\sigma_u^2} - \frac{1}{\lambda_{u_i}}\right), \quad (\text{S4.199})$$

uniformly in  $1 \leq i \leq m$ , and

$$\frac{1}{m}\sum_{i=1}^m \alpha\{Y_{ij}\exp(-\mathbf{X}_{ij}^T\boldsymbol{\beta}^c - \hat{\underline{\mu}}_{v_j} + \hat{\underline{\lambda}}_{v_j}/2) - 1\} = \frac{\hat{\underline{\mu}}_{v_j}}{m\sigma_v^2}, \quad (\text{S4.200})$$

and

$$-\frac{1}{m}\sum_{i=1}^m \alpha Y_{ij}\exp(\hat{\underline{\lambda}}_{v_j}/2 - \mathbf{X}_{ij}^T\boldsymbol{\beta}^c - \hat{\underline{\mu}}_{v_j}) = \frac{1}{m}\left(\frac{1}{\sigma_v^2} - \frac{1}{\lambda_{v_j}}\right), \quad (\text{S4.201})$$

uniformly in  $1 \leq j \leq n$ , where  $(\beta_1^r, \beta_1^c, \beta_{-1}, \sigma_u^2, \sigma_v^2) = [-2C_1, 2C_1] \times [-2C_1, C_1] \times [C_1^{-1}, C_1]^{p-1} \times [C_1^{-1}, C_1]$ . By (S4.196), (S4.198) and (S4.199) can be written as

$$\begin{aligned} & \exp(\beta_1^{r0} - \beta_1^r + U_i - \hat{\mu}_i + \hat{\lambda}_{u_i}/2) \phi(\beta_{-1}^0 - \beta_{-1}) + O_p(n^{-\rho}) - 1 \\ &= \frac{\hat{\mu}_{u_i}}{n\alpha\sigma_u^2}, \end{aligned} \quad (\text{S4.202})$$

and

$$\begin{aligned} & \exp(\beta_1^{r0} - \beta_1^r + U_i - \hat{\mu}_i + \hat{\lambda}_{u_i}/2) \phi(\beta_{-1}^0 - \beta_{-1}) + O_p(n^{-\rho}) \\ &= \frac{1}{n\alpha\hat{\lambda}_{u_i}} - \frac{1}{n\alpha\sigma_u^2} \end{aligned} \quad (\text{S4.203})$$

where the remainders  $O_p(\cdot)$  are of the stated orders uniformly in  $1 \leq i \leq m$  and in  $(\beta_1^r, \beta_{-1}, \sigma_u^2) \in [-2C_1, 2C_1] \times [-C_1, C_1]^{p-1} \times [C_1^{-1}, C_1]$ . By (S4.202), we have

$$\begin{aligned} & \exp(\beta_1^{r0} + U_i) \phi(\beta_{-1}^0 - \beta_{-1}) \\ &= \{1 + \mu_{u_i}/(n\alpha\sigma_u^2) + O_p(n^{-\rho})\} \exp(\beta_1^r + \mu_{u_i} - \lambda_{u_i}/2) \end{aligned} \quad (\text{S4.204})$$

By (S4.193),  $\lambda_{u_i} < \sigma_u^2$ . Therefore, the term  $\exp(\beta_1^r + \mu_{u_i} - \lambda_{u_i}/2)$  in the right-hand side of (S4.204) equals  $\exp(\mu_{u_i} + \omega_i)$ , where  $\beta_1^r - \sigma_u^2/2 \leq \omega_i \leq \beta_1^r + \sigma_u^2/2$ . Since  $\sigma_u^2$  and  $\beta_1^r$  are in compact sets and bounded,  $|\omega_i|$  is bounded uniformly in  $i$ . We can show that  $\mu_{u_i} \exp(\mu_{u_i} + \omega_i)/(n\alpha\sigma_u^2) = o_p(1)$  we call this result R1. If R1 fails for some  $\eta > 0$ , then it can be shown that "for some

$i \in \{1, 2, \dots, m\}$ , both  $\mu_{u_i} > 0$  and  $\mu_{u_i} \exp(\mu_{u_i} + \omega_i)/(n\alpha\sigma_u^2) > \eta$ , for all  $\sigma_u^2$ ,  $\beta_1^r$ , and  $\beta_1$  satisfying  $\sigma_u^2, |\beta_0^r|, |\beta_k| \leq C_1, k = 2, \dots, p$ , and  $\sigma_u^2 > C_1^{-1}$ ." Since  $|\omega_i|$  is bounded then  $\mu_{u_i} > \log n + O_p(\log \log n)$ , and  $\phi(\beta_{-1}^0 - \beta_{-1})$  is bounded away from zero and infinity uniformly in  $\beta_{-1}^0 \in [-C_1, C_1]^{p-1}$ , so for this  $i$ , the term  $\mu_{u_i}$  in the right-hand side of (S4.204) is of order  $n^c$  for some  $c > 0$ . Hence for this  $i$ ,  $\exp(\beta_1^{r0} + U_i) = O_p(n^c)$ , and so the probability that the latter bound holds for some  $i \in \{1, 2, \dots, m\}$  must itself be bounded away from zero along an infinite subsequence of values of  $n$  diverging to infinity; call this result R2. Since  $P[\max_{1 \leq i \leq m} \exp(U_i) > \exp\{C(\log n)^{1/2}\}] \rightarrow 0$ . Since  $\exp\{C(\log n)^{1/2}\}$  is of strictly less order than  $n^c$  for any  $c > 0$ , property R2 is violated, and so R1 must be true.

Combining R1 and (S4.202) we have

$$\exp(\beta_1^{r0} - \beta_1^r + U_i - \hat{\underline{\mu}}_i + \hat{\underline{\lambda}}_{u_i}/2)\phi(\beta_{-1}^0 - \beta_{-1}) = 1 + o_p(1) \quad (\text{S4.205})$$

uniformly in  $1 \leq i \leq m$ . Taking logarithms of both sides of (S4.205), we have

$$\beta_1^{r0} - \beta_1^r + U_i - \hat{\underline{\mu}}_i + \hat{\underline{\lambda}}_{u_i}/2 + \log\{\phi(\beta_{-1}^0 - \beta_{-1})\} = o_p(1) \quad (\text{S4.206})$$

uniformly in  $1 \leq i \leq m$ . By (S4.203), we have

$$\begin{aligned} \hat{\underline{\lambda}}_{u_i} &= [\sigma_u^{-2} + n\alpha\{\exp(\beta_1^{r0} - \beta_1^r + U_i - \hat{\underline{\mu}}_i + \hat{\underline{\lambda}}_{u_i}/2)\phi(\beta_{-1}^0 - \beta_{-1}) \\ &\quad + O_p(n^{1-\rho})\}]^{-1}. \end{aligned} \quad (\text{S4.207})$$

uniformly in  $1 \leq i \leq m$ , for any  $\rho \in (0, 1/2)$ . Substituting (S4.205) into (S4.207), we have

$$\widehat{\underline{\lambda}}_{u_i} = [\sigma_u^{-2} + n\alpha\{1 + o_p(1) + O_p(n^{1-\rho})\}]^{-1} = O_p(n^{-1}). \quad (\text{S4.208})$$

uniformly in  $1 \leq i \leq m$ . Combining (S4.206) and (S4.208) we have

$$\widehat{\underline{\mu}}_{u_i} = \beta_1^{r0} - \beta_1^r + U_i + \log\{\phi(\beta_{-1}^0 - \beta_{-1})\} + o_p(1). \quad (\text{S4.209})$$

uniformly in  $1 \leq i \leq m$ . Similarly, we can derive that

$$\widehat{\underline{\lambda}}_{v_j} = [\sigma_v^{-2} + m\alpha\{1 + o_p(1)\} + O_p(m^{1-\rho})]^{-1} = O_p(m^{-1}), \quad (\text{S4.210})$$

$$\widehat{\underline{\mu}}_{v_j} = \beta_1^{c0} - \beta_1^c + V_j + \log\{\phi(\beta_{-1}^0 - \beta_{-1})\} + o_p(1). \quad (\text{S4.211})$$

uniformly in  $1 \leq j \leq n$ . Combining (S4.190), (S4.192), (S4.209), and (S4.211) we have

$$\beta_1^{r0} - \widehat{\underline{\beta}}_1^r + \log\{\phi(\beta_{-1}^0 - \widehat{\underline{\beta}}_{-1})\} = o_p(1), \quad (\text{S4.212})$$

$$\beta_1^{c0} - \widehat{\underline{\beta}}_1^c + \log\{\phi(\beta_{-1}^0 - \widehat{\underline{\beta}}_{-1})\} = o_p(1). \quad (\text{S4.213})$$

Combining (S4.176), (S4.197), and (S4.206) we have

$$\begin{aligned} & \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \alpha \{Y_{ij} \exp(-\mathbf{X}_{ij}^\top \beta^r - \mu_{u_i} + \lambda_{u_i}/2) - 1\} \mathbf{X}_{ij,-1} \\ & + \frac{1}{mn} \sum_{j=1}^n \sum_{i=1}^m \alpha \{Y_{ij} \exp(-\mathbf{X}_{ij}^\top \beta^c - \mu_{v_j} + \lambda_{v_j}/2) - 1\} \mathbf{X}_{ij,-1} \\ & = \frac{2\alpha\{1 + o_p(1)\}}{\phi(\beta_{-1}^0 - \beta_{-1})} \{\phi_1(\beta_{-1}^0 - \beta_{-1}) + m^{-\rho} + n^{-\rho}\} - \frac{2\alpha}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} \\ & = \frac{2\alpha\phi_1(\beta_{-1}^0 - \beta_{-1})}{\phi(\beta_{-1}^0 - \beta_{-1})} - 2\alpha\boldsymbol{\mu}_{X_{-1}} + o_p(1). \end{aligned} \quad (\text{S4.214})$$

By Taylor's expansion of  $\phi_1(\beta_{-1}^0 - \beta_{-1})/\phi(\beta_{-1}^0 - \beta_{-1})$ , we have

$$\frac{\phi_1(\beta_{-1}^0 - \beta_{-1})}{\phi(\beta_{-1}^0 - \beta_{-1})} = \mu_{X_{-1}} + \Sigma_{X_{-1}}(\beta_{-1}^0 - \beta_{-1}) + o_p(1). \quad (\text{S4.215})$$

By the assumption (A9) and (S4.214), (S4.215) implies that the consistency of  $\widehat{\underline{\beta}}_{-1}$ . Combining (S4.212), (S4.213) with (S4.214), respectively, we obtain the consistency of  $\widehat{\underline{\beta}}_1^r$  and  $\widehat{\underline{\beta}}_1^c$ .

Note that results (S4.183), (S4.208), and (S4.209) imply

$$\widehat{\underline{\sigma}}_u^2 = \frac{1}{m} \sum_{i=1}^m [U_i + \beta_1^{r0} - \beta_1^r + \log\{\phi(\beta_{-1}^0 - \beta_{-1})\}]^2 + o_p(1),$$

by consistency of  $\widehat{\underline{\beta}}_1^r$  and  $\widehat{\underline{\beta}}_{-1}$ , and  $m^{-1} \sum_{i=1}^m U_i^2 = (\sigma_u^2)^0 + O_p(m^{-1/2})$ , further we have

$$\widehat{\underline{\sigma}}_u^2 = (\sigma_u^2)^0 + o_p(1), \quad (\text{S4.216})$$

which implies  $\widehat{\underline{\sigma}}_u^2$  is consistent.

For the consistency of  $\widehat{\underline{\sigma}}_v^2$ , it can be derived analogously:

$$\widehat{\underline{\sigma}}_v^2 = \frac{1}{n} \sum_{j=1}^n V_j^2 + o_p(1) = (\sigma_v^2)^0 + o_p(1). \quad (\text{S4.217})$$

Since  $\beta_1^{r0} = \beta_1^0 + (\sigma_v^2)^0/2$  and  $\beta_1^{c0} = \beta_1^0 + (\sigma_u^2)^0/2$ , we have

$$\beta_1^0 = \frac{1}{2} \left\{ \beta_1^{r0} - \frac{(\sigma_v^2)^0}{2} + \beta_1^{c0} - \frac{(\sigma_u^2)^0}{2} \right\} \quad (\text{S4.218})$$

and can define the estimator of  $\beta_1^0$  by

$$\widehat{\underline{\beta}}_1 = \frac{1}{2} \left( \widehat{\underline{\beta}}_1^r - \frac{\widehat{\underline{\sigma}}_v^2}{2} + \widehat{\underline{\beta}}_1^c - \frac{\widehat{\underline{\sigma}}_u^2}{2} \right). \quad (\text{S4.219})$$

Equations (S4.212), (S4.213), (S4.216)-(S4.219) imply that

$$\widehat{\underline{\beta}}_1 = \beta_1^0 + o_p(1),$$

and  $\beta_1^0$  can be estimated consistently.

#### S4.2 Convergence rate for variational estimators

Since (S4.175) and the results of consistency, we can define  $\Delta_{i,1}$  by

$$\begin{aligned} & \frac{1}{n} \sum_{j=1}^n Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^r) \\ &= \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1}) \exp(\beta_1^{r0} - \beta_1^r + U_i + \Delta_{i,1}), \end{aligned} \quad (\text{S4.220})$$

uniformly in  $1 \leq i \leq m$ ; similarly, we also can define  $\Delta'_{j,1}$  by

$$\frac{1}{m} \sum_{i=1}^m Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^c) = \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1}) \exp(\beta_1^{c0} - \beta_1^c + V_j + \Delta'_{j,1}),$$

uniformly in  $1 \leq j \leq m$ . By Taylor's expansion of  $\exp(\Delta_{i,1})$  and (S4.220),

we have

$$\begin{aligned} & \frac{1}{n} \sum_{j=1}^n Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^r - U_i) - \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1}) \exp(\beta_1^{r0} - \beta_1^r) \\ &= \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1}) \exp(\beta_1^{r0} - \beta_1^r) \left\{ \Delta_{i,1} + \frac{1}{2} \Delta_{i,1}^2 + O_p(\Delta_{i,1}^3) \right\}. \end{aligned}$$

uniformly in  $1 \leq i \leq m$ . Therefore,

$$\begin{aligned} & \Delta_{i,1} + \frac{1}{2} \Delta_{i,1}^2 + O_p(\Delta_{i,1}^3) \\ &= \frac{1}{n\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} \sum_{j=1}^n Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) - \quad (\text{S4.221}) \end{aligned}$$

uniformly in  $1 \leq i \leq m$ . By (S4.221) and the following fact, for each  $\epsilon > 0$

$$E \left\{ \frac{1}{n\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} \sum_{j=1}^n Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) - 1 \right\}^2 = O_p(n^{\epsilon-1})$$

uniformly in  $1 \leq i \leq m$ , we deduce that  $\Delta_{i,1}$  satisfies, for all  $C > 0$  and each  $\rho \in (0, 1/2)$ ,

$$\max_{1 \leq i \leq m} \sup_{\|\beta_1^0\|, \|\beta_1\| \leq C_1} |\Delta_{i,1}| = O_p(n^{-\rho}), \quad (\text{S4.222})$$

Similarly, we can deduce that  $\Delta'_{j,1}$  satisfies, for all  $C > 0$  and each  $\rho \in (0, 1/2)$ ,

$$\max_{1 \leq j \leq n} \sup_{\|\beta_1^0\|, \|\beta_1\| \leq C_1} |\Delta'_{j,1}| = O_p(m^{-\rho}). \quad (\text{S4.223})$$

Squaring both sides of (S4.221),

$$\begin{aligned} \Delta_{i,1}^2 &= \left\{ \frac{1}{n\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} \sum_{j=1}^n Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) - 1 \right\}^2 \\ &\quad + O_p(n^{\epsilon-3/2}) \end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ .

$$\begin{aligned}
& \frac{1}{m} \sum_{i=1}^m E(\Delta_{i,1}^2) \\
&= \frac{1}{m} \sum_{i=1}^m E \left\{ \frac{1}{n\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} \sum_{j=1}^n Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) - 1 \right\}^2 \\
&= \frac{1}{n^2 \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})^2} \\
&\quad \times E \left[ \sum_{j=1}^n \{Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) - \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})\} \right]^2 \\
&= \frac{1}{n\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})^2} \left[ \frac{1}{\alpha} \phi(2\boldsymbol{\beta}_{-1}^0 - 2\boldsymbol{\beta}_{-1}) \exp\{(\sigma_v^2)^0\} - \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})^2 \right] \\
&= O_p(n^{-1}),
\end{aligned}$$

we also have

$$\begin{aligned}
\frac{1}{m} \sum_{i=1}^m \Delta_{i,1} &= \frac{1}{mn\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} \sum_{i=1}^m \sum_{j=1}^n Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) \\
&\quad - 1 + O_p(n^{-1}).
\end{aligned}$$

Since

$$\begin{aligned}
& E \left\{ \frac{1}{mn\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} \sum_{i=1}^m \sum_{j=1}^n Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) - 1 \right\}^2 \\
&= \frac{1}{m^2 n^2 \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})^2} \sum_{i=1}^m \sum_{j=1}^n Y_{ij}^2 \exp(-2\beta_1^{r0} - 2\mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - 2U_i) \\
&\quad + \frac{1}{m^2 n^2 \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})^2} \\
&\quad \times \sum_{i=1}^m \sum_{k \neq i}^m \sum_{j=1}^n Y_{ij} Y_{kj} \exp(-2\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - \mathbf{X}_{kj,-1}^T \boldsymbol{\beta}_{-1} - U_i - U_k) \\
&\quad + \frac{1}{m^2 n^2 \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})^2} \\
&\quad \times \sum_{i=1}^m \sum_{j=1}^n \sum_{l \neq j}^n Y_{ij} Y_{il} \exp(-2\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - \mathbf{X}_{il,-1}^T \boldsymbol{\beta}_{-1} - 2U_i) \\
&\quad + \frac{1}{m^2 n^2 \phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})^2} \\
&\quad \times \sum_{i=1}^m \sum_{k \neq i}^m \sum_{j=1}^n \sum_{l \neq j}^n Y_{ij} Y_{kl} \exp(-2\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - \mathbf{X}_{kl,-1}^T \boldsymbol{\beta}_{-1} - U_i - U_k) - 1 \\
&= \frac{\phi(2\boldsymbol{\beta}_{-1}^0 - 2\boldsymbol{\beta}_{-1})}{mn\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})^2} \frac{1}{\alpha} \exp\{(\sigma_v^2)^0\} + \frac{m-1}{mn} \exp\{(\sigma_v^2)^0\} \\
&\quad + \frac{n-1}{mn} + \frac{(n-1)(m-1)}{mn} - 1 \\
&= \frac{1}{n} [\exp\{(\sigma_v^2)^0\} - 1] + O_p(m^{-1}n^{-1}),
\end{aligned}$$

we can deduce that

$$\frac{1}{m} \sum_{i=1}^m \Delta_{i,1} = O_p\{(mn)^{-1/2} + n^{-1/2}\}. \quad (\text{S4.224})$$

The following property can be derived analogously:

$$\frac{1}{n} \sum_{j=1}^n \Delta'_{j,1} = O_p\{(mn)^{-1/2} + m^{-1/2}\}. \quad (\text{S4.225})$$

Furthermore, this fact

$$\begin{aligned} E \left( \frac{1}{m} \sum_{i=1}^m U_i \Delta_{i,1} \right)^2 &= \frac{\phi(2\boldsymbol{\beta}_{-1}^0 - 2\boldsymbol{\beta}_{-1})}{mn\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})^2} \frac{1}{\alpha} (\sigma_u^2)^0 \exp\{(\sigma_v^2)^0\} - \frac{1}{mn} (\sigma_u^2)^0 \\ &= O_p(m^{-1}n^{-1}), \end{aligned} \quad (\text{S4.226})$$

implies that

$$\frac{1}{m} \sum_{i=1}^m U_i \Delta_{i,1} = O_p(m^{-1/2}n^{-1/2}).$$

The same property is true for  $\sum_{j=1}^n V_j \Delta'_{j,1}/n$ ,

$$\frac{1}{n} \sum_{j=1}^n V_j \Delta'_{j,1} = O_p(m^{-1/2}n^{-1/2}).$$

Based on the notations of (S4.220) and (S4.221), (S4.198) is equivalent

to

$$\begin{aligned} &\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1}) \exp(\beta_1^{r0} - \beta_1^r + U_i + \Delta_{i,1} - \widehat{\underline{\mu}}_{u_i} + \widehat{\underline{\lambda}}_{u_i}/2) \\ &= 1 + \frac{\widehat{\underline{\mu}}_{u_i}}{n\alpha\sigma_u^2}, \end{aligned} \quad (\text{S4.227})$$

and (S4.200) is equivalent to

$$\begin{aligned} &\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1}) \exp(\beta_1^{c0} - \beta_1^c + V_j + \Delta'_{j,1} - \widehat{\underline{\mu}}_{v_j} + \widehat{\underline{\lambda}}_{v_j}/2) \\ &= 1 + \frac{\widehat{\underline{\mu}}_{v_j}}{m\alpha\sigma_v^2}. \end{aligned} \quad (\text{S4.228})$$

Taking logarithms of both sides of (S4.227) and (S4.228), respectively, we

have

$$\begin{aligned} & \log\{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})\} + \beta_1^{r0} - \beta_1^r + U_i + \Delta_{i,1} - \widehat{\underline{\mu}}_{u_i} + \widehat{\underline{\lambda}}_{u_i}/2 \\ &= \frac{\widehat{\underline{\mu}}_{u_i}}{n\alpha\sigma_u^2} + o_p(n^{-1}), \end{aligned} \quad (\text{S4.229})$$

and

$$\begin{aligned} & \log\{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})\} + \beta_1^{c0} - \beta_1^c + V_j + \Delta'_{j,1} - \widehat{\underline{\mu}}_{v_j} + \widehat{\underline{\lambda}}_{v_j}/2 \\ &= \frac{\widehat{\underline{\mu}}_{v_j}}{m\alpha\sigma_v^2} + o_p(m^{-1}), \end{aligned} \quad (\text{S4.230})$$

Adding (S4.229) over  $i$  and adding (S4.230) over  $j$ ,  $\beta_0^r, \beta_0^c$ , and  $\beta_1$  satisfy the following equations,

$$\begin{aligned} & \beta_1^{r0} - \beta_1^r + \log\{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})\} \\ &= -\frac{1}{m} \sum_{i=1}^m (U_i + \Delta_{i,1} - \widehat{\underline{\mu}}_{u_i} + \widehat{\underline{\lambda}}_{u_i}/2), \end{aligned} \quad (\text{S4.231})$$

and

$$\begin{aligned} & \beta_1^{c0} - \beta_1^c + \log\{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})\} \\ &= -\frac{1}{n} \sum_{j=1}^n (V_j + \Delta'_{j,1} - \widehat{\underline{\mu}}_{v_j} + \widehat{\underline{\lambda}}_{v_j}/2). \end{aligned} \quad (\text{S4.232})$$

By  $m^{-1} \sum_{i=1}^m U_i = O_p(m^{-1/2})$ , (S4.190), (S4.224), (S4.225), and (S4.208),

we have

$$\beta_1^{r0} - \widehat{\underline{\beta}}_1^r + \log\{\phi(\boldsymbol{\beta}_{-1}^0 - \widehat{\underline{\beta}}_{-1})\} = O_p(m^{-1/2} + n^{-1/2}), \quad (\text{S4.233})$$

$$\beta_1^{c0} - \widehat{\underline{\beta}}_1^c + \log\{\phi(\boldsymbol{\beta}_{-1}^0 - \widehat{\underline{\beta}}_{-1})\} = O_p(m^{-1/2} + n^{-1/2}). \quad (\text{S4.234})$$

Setting equation (S4.176) equal to zero we have

$$\begin{aligned} & \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^r - \mu_{u_i} + \lambda_{u_i}/2) - 1\} \quad (\text{S4.235}) \\ & + \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^c - \mu_{v_j} + \lambda_{v_j}/2) - 1\} = 0. \end{aligned}$$

Combining (S4.229), (S4.230), (S4.234), and (S4.235) we have

$$\begin{aligned} 0 &= \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^r - \mu_{u_i} + \lambda_{u_i}/2) - 1\} \\ &+ \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^c - \mu_{v_j} + \lambda_{v_j}/2) - 1\} \\ &= \frac{\exp(O_p\{(mn)^{\epsilon-1/2} + n^{\epsilon-1} + n^{-1}\})}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} \\ &\quad \times \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) \\ &\quad + \frac{\exp(O_p\{(mn)^{\epsilon-1/2} + m^{\epsilon-1} + m^{-1}\})}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} \\ &\quad \times \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} Y_{ij} \exp(-\beta_1^{c0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - V_j) \\ &\quad - 2\boldsymbol{\mu}_{X_{-1} + O_p(m^{-1/2}n^{-1/2})} \\ &= \frac{1 + O_p\{(mn)^{\epsilon-1/2} + n^{\epsilon-1}\}}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} \{\phi_1(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1}) + O_p(n^{-1/2})\} \\ &\quad + \frac{1 + O_p\{(mn)^{\epsilon-1/2} + m^{\epsilon-1}\}}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} \{\phi_1(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1}) + O_p(m^{-1/2})\} - 2\boldsymbol{\mu}_{X_{-1}} \\ &= \frac{2\phi_1(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} - 2\boldsymbol{\mu}_{X_{-1}} + O_p(m^{-1/2} + n^{-1/2}), \end{aligned}$$

which implies that

$$\hat{\boldsymbol{\beta}}_{-1} - \boldsymbol{\beta}_{-1}^0 = O_p(m^{-1/2} + n^{-1/2}). \quad (\text{S4.236})$$

Combining (S4.233), (S4.234), and (S4.236) we have

$$\widehat{\underline{\beta}}_1^r - \beta_1^{r0} = O_p(m^{-1/2} + n^{-1/2}), \quad (\text{S4.237})$$

$$\widehat{\underline{\beta}}_1^c - \beta_1^{c0} = O_p(m^{-1/2} + n^{-1/2}). \quad (\text{S4.238})$$

By (S4.208), (S4.229), and (S4.233), we have

$$\widehat{\underline{\mu}}_{u_i} = U_i + \Delta_{i,1} + O_p(m^{-1/2} + n^{-1/2}), \quad (\text{S4.239})$$

uniformly in  $1 \leq i \leq m$ . By (S4.222) and (S4.239), we deduce that

$$\begin{aligned} \frac{1}{m} \sum_{i=1}^m \widehat{\underline{\mu}}_{u_i}^2 &= \frac{1}{m} \sum_{i=1}^m U_i^2 + O_p(m^{-1/2} + n^{-1/2}) \\ &= (\sigma_u^2)^0 + O_p(m^{-1/2} + n^{-1/2}). \end{aligned} \quad (\text{S4.240})$$

By (S4.210), (S4.230), and (S4.234), we deduce that

$$\widehat{\underline{\mu}}_{v_j} = V_j + \Delta'_{j,1} + O_p(m^{-1/2} + n^{-1/2}), \quad (\text{S4.241})$$

uniformly in  $1 \leq j \leq n$ . By (S4.223) and (S4.241), we deduce that

$$\begin{aligned} \frac{1}{n} \sum_{j=1}^n \widehat{\underline{\mu}}_{v_j}^2 &= \frac{1}{n} \sum_{j=1}^n V_j^2 + O_p(m^{-1/2} + n^{-1/2}) \\ &= (\sigma_v^2)^0 + O_p(m^{-1/2} + n^{-1/2}). \end{aligned} \quad (\text{S4.242})$$

Combining (S4.183), (S4.208), and (S4.240) we deduce that

$$\widehat{\underline{\sigma}}_u^2 = (\sigma_u^2)^0 + O_p(m^{-1/2} + n^{-1/2}), \quad (\text{S4.243})$$

and combining (S4.184), (S4.210), and (S4.242) we deduce that

$$\widehat{\underline{\sigma}}_v^2 = (\sigma_v^2)^0 + O_p(m^{-1/2} + n^{-1/2}). \quad (\text{S4.244})$$

Together, (S4.218), (S4.219), (S4.237), (S4.238), (S4.243), and (S4.244) give

$$\begin{aligned}\widehat{\underline{\beta}}_1 - \beta_1^0 &= \frac{1}{2} \left\{ \widehat{\underline{\beta}}_1^r - \beta_1^{r0} - \frac{\widehat{\sigma}_v^2 - (\sigma_v^2)^0}{2} + \widehat{\underline{\beta}}_1^c - \beta_1^{c0} - \frac{\widehat{\sigma}_u^2 - (\sigma_u^2)^0}{2} \right\} \\ &= O_p(m^{-1/2} + n^{-1/2}).\end{aligned}$$

This completes the proof of consistency at the rate  $m^{-1/2} + n^{-1/2}$  for the Gamma regression model in Theorem 1.

## S5 Proof of Theorem 2 for Gamma regression model

For Gamma case, the proof of Theorem 2 includes 3 steps:

Step1. initial approximation to  $\widehat{\underline{\beta}}_1^r - \beta_1^{r0}$ ,  $\widehat{\underline{\beta}}_1^c - \beta_1^{c0}$ , and  $\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0$  in §S5.1;

Step2. Final approximations to  $\widehat{\sigma}_u^2 - (\sigma_u^2)^0$  and  $\widehat{\sigma}_v^2 - (\sigma_v^2)^0$  in §S5.2;

Step3. Final approximations to  $\widehat{\underline{\beta}}_1 - \beta_1^0$  and  $\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0$  in §S5.3.

### S5.1 Initial approximation to $\widehat{\underline{\beta}}_1^r - \beta_1^{r0}$ , $\widehat{\underline{\beta}}_1^c - \beta_1^{c0}$ and $\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0$

Denote  $\boldsymbol{\mu}_{\mathbf{X}_{-1}}$  and  $\Sigma_{\mathbf{X}_{-1}}^2$  the mean and variance of  $\mathbf{X}_{-1}$ . Equating (S4.176)

to zero we have

$$\begin{aligned}& \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \widehat{\underline{\beta}}^r - \widehat{\underline{\mu}}_{u_i} + \widehat{\lambda}_{u_i}/2) \\ & + \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \widehat{\underline{\beta}}^c - \widehat{\underline{\mu}}_{v_j} + \widehat{\lambda}_{v_j}/2) \\ & - \frac{2}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} = 0.\end{aligned}\tag{S5.245}$$

By (S4.236), (S5.245), and Taylor expansions of  $\exp\{\mathbf{X}_{ij,-1}^T(\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1})\}$

$$\begin{aligned}
 & \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} Y_{ij} \exp(-\widehat{\underline{\beta}}_1^r - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0 - \widehat{\underline{\mu}}_{u_i} + \widehat{\underline{\lambda}}_{u_i}/2) \\
 & + \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n Y_{ij} \exp(-\widehat{\underline{\beta}}_1^r - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0 - \widehat{\underline{\mu}}_{u_i} + \widehat{\underline{\lambda}}_{u_i}/2) \\
 & \times \mathbf{X}_{ij,-1} \mathbf{X}_{ij,-1}^T (\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1}) \\
 & + \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} Y_{ij} \exp(-\widehat{\underline{\beta}}_1^c - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0 - \widehat{\underline{\mu}}_{v_j} + \widehat{\underline{\lambda}}_{v_j}/2) \\
 & + \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n Y_{ij} \exp(-\widehat{\underline{\beta}}_1^c - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1}^0 - \widehat{\underline{\mu}}_{v_j} + \widehat{\underline{\lambda}}_{v_j}/2) \\
 & \times \mathbf{X}_{ij,-1} \mathbf{X}_{ij,-1}^T (\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1}) \\
 & = \frac{2}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} + O_p\{\|\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1}\|^2\}. \tag{S5.246}
 \end{aligned}$$

Since (S4.229) imply that

$$\begin{aligned}
 \widehat{\underline{\mu}}_{u_i} \left(1 + \frac{1}{n\alpha\sigma_u^2}\right) &= U_i + \Delta_{i,1} + \frac{1}{2}\widehat{\underline{\lambda}}_{u_i} + \beta_1^{r0} - \widehat{\underline{\beta}}_1^r \\
 &+ \log\{\phi(\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1})\}, \tag{S5.247}
 \end{aligned}$$

uniformly in  $1 \leq i \leq m$ , for each  $\epsilon > 0$ , adding (S5.247) over  $i$  and dividing

both sides by  $m$ , we have

$$\begin{aligned}
 & \frac{1}{m} \sum_{i=1}^m \widehat{\underline{\mu}}_{u_i} \left(1 + \frac{1}{n\alpha\sigma_u^2}\right) \tag{S5.248} \\
 &= \frac{1}{m} \sum_{i=1}^m [U_i + \Delta_{i,1} + \frac{1}{2}\widehat{\underline{\lambda}}_{u_i} + \beta_1^{r0} - \widehat{\underline{\beta}}_1^r + \log\{\phi(\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1})\}].
 \end{aligned}$$

Substituting the (S4.190) into (S5.248) we deduce that

$$\widehat{\underline{\beta}}_1^r = \beta_1^{r0} + \bar{U} + \bar{\Delta}_{i,1} + \log\{\phi(\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1})\}. \tag{S5.249}$$

By (S5.247), (S4.208), and (S4.231), we have

$$\hat{\underline{\mu}}_{u_i} = (U_i + \Delta_{i,1} - \bar{U} - \bar{\Delta}_{i,1}) \left\{ 1 - \frac{1}{n\alpha\sigma_u^2} + \frac{2}{n^2\alpha^2\sigma_u^4} \right\}. \quad (\text{S5.250})$$

Combining (S4.210), (S4.211), and (S4.232) we can derive analogous properties,

$$\widehat{\underline{\beta}}_1^c = \beta_1^{c0} + \bar{V} + \bar{\Delta}'_{j,1} + \log\{\phi(\beta_{-1}^0 - \widehat{\underline{\beta}}_{-1})\}, \quad (\text{S5.251})$$

$$\hat{\underline{\mu}}_{v_j} = (V_j + \Delta'_{j,1} - \bar{V} - \bar{\Delta}'_{j,1})\{1 + O_p(m^{-1})\}. \quad (\text{S5.252})$$

Substituting the (S5.249), (S5.250), (S5.251), and (S5.252) into (S5.246)

we have

$$\begin{aligned} & \frac{1}{mn\phi(\beta_{-1}^0 - \widehat{\underline{\beta}}_{-1})} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \beta^{r0} - U_i - \Delta_{i,1} - \frac{U_i}{n\alpha\sigma_u^2}) \\ & + \frac{\exp\{O_p(n^{\epsilon-1})\}}{mn\phi(\beta_{-1}^0 - \widehat{\underline{\beta}}_{-1})} \sum_{i=1}^m \sum_{j=1}^n Y_{ij} \exp(-\mathbf{X}_{ij}^T \beta^{r0} - U_i - \Delta_{i,1}) \\ & \times \mathbf{X}_{ij,-1} \mathbf{X}_{ij,-1}^T (\beta_{-1}^0 - \widehat{\underline{\beta}}_{-1}) \\ & + \frac{1}{mn\phi(\beta_{-1}^0 - \widehat{\underline{\beta}}_{-1})} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \beta^{c0} - V_j - \Delta'_{j,1} - \frac{V_j}{m\alpha\sigma_v^2}) \\ & + \frac{\exp\{O_p(m^{\epsilon-1})\}}{mn\phi(\beta_{-1}^0 - \widehat{\underline{\beta}}_{-1})} \sum_{i=1}^m \sum_{j=1}^n Y_{ij} \exp(-\mathbf{X}_{ij,-1}^T \beta^{c0} - V_j - \Delta'_{j,1}) \\ & \times \mathbf{X}_{ij,-1} \mathbf{X}_{ij,-1}^T (\beta_{-1}^0 - \widehat{\underline{\beta}}_{-1}) \\ & = \frac{2}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1}, \end{aligned}$$

by  $\exp\{O_p(n^{\epsilon-1})\} = 1 + O_p(n^{\epsilon-1})$  and  $\exp(-\Delta_{i,1}) = 1 - \Delta_{i,1} + O_p(n^{\epsilon-1})$ ,

$$\begin{aligned}
 & \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} - U_i) \mathbf{X}_{ij,-1} \mathbf{X}_{ij,-1}^T (\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1}) \\
 & + \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{c0} - V_j) \mathbf{X}_{ij,-1} \mathbf{X}_{ij,-1}^T (\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1}) \\
 & + O_p\{m^{\epsilon-3/2} + n^{\epsilon-3/2}\} \\
 & + \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1}^T Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} - U_i) (1 - \Delta_{i,1}) + O_p(m^{\epsilon-3/2}) \\
 & + \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1}^T Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{c0} - V_j) (1 - \Delta'_{j,1}) + O_p(n^{\epsilon-3/2}) \\
 & = \phi(\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1}) \frac{2}{mn} \sum_{i=1}^m \sum_{j=1}^n \mathbf{X}_{ij,-1}. \tag{S5.253}
 \end{aligned}$$

By the law of large numbers, we deduce that

$$\begin{aligned}
 & \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} - U_i) \mathbf{X}_{ij,-1} \mathbf{X}_{ij,-1}^T \\
 & = \boldsymbol{\mu}_{\mathbf{X}_{-1}} \boldsymbol{\mu}_{\mathbf{X}_{-1}}^T + \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} + o_p(1), \tag{S5.254}
 \end{aligned}$$

and

$$\begin{aligned}
 & \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{c0} - V_j) \mathbf{X}_{ij,-1} \mathbf{X}_{ij,-1}^T \\
 & = \boldsymbol{\mu}_{\mathbf{X}_{-1}} \boldsymbol{\mu}_{\mathbf{X}_{-1}}^T + \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} + o_p(1). \tag{S5.255}
 \end{aligned}$$

Using Taylor's expansion to  $\phi(\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1})$  we have

$$\begin{aligned}
 & \phi(\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1}) \\
 & = 1 + \boldsymbol{\mu}_{\mathbf{X}_{-1}}^T (\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1}) \\
 & \quad + (\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1})^T (\boldsymbol{\mu}_{\mathbf{X}_{-1}} \boldsymbol{\mu}_{\mathbf{X}_{-1}}^T + \boldsymbol{\Sigma}_{\mathbf{X}_{-1}}) (\boldsymbol{\beta}_{-1}^0 - \hat{\boldsymbol{\beta}}_{-1}). \tag{S5.256}
 \end{aligned}$$

Substituting (S5.254), (S5.255), and (S5.256) into (S5.253) we have

$$\begin{aligned}
& 2\Sigma_{\mathbf{X}_{-1}}(\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0) \\
&= T_1 + T_2 + T_3 + T_4 + o_p\{m^{-1/2}n^{-1/2} + \|\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0\|^2\}. \quad (\text{S5.257})
\end{aligned}$$

where

$$\begin{aligned}
T_1 &= \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \{\mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \beta^{r0} - U_i) - \mathbf{X}_{ij,-1}\} - \frac{\mu_{\mathbf{X}_{-1}}}{m} \sum_{i=1}^m S_1, \\
T_2 &= \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \{\mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \beta^{c0} - V_j) - \mathbf{X}_{ij,-1}\} - \frac{\mu_{\mathbf{X}_{-1}}}{n} \sum_{j=1}^n S_2, \\
T_3 &= -\frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \{\mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \beta^{r0} - U_i) - \mu_{\mathbf{X}_{-1}}\} S_1 + \frac{\mu_{\mathbf{X}_{-1}}}{m} \sum_{i=1}^m S_1^2, \\
T_4 &= -\frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \{\mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \beta^{c0} - V_j) - \mu_{\mathbf{X}_{-1}}\} S_2 + \frac{\mu_{\mathbf{X}_{-1}}}{n} \sum_{j=1}^n S_2^2.
\end{aligned}$$

Notice that

$$E(T_3) = O_p\{n^{-1}\|\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0\|^2\}, \quad (\text{S5.258})$$

$$E(T_4) = O_p\{m^{-1}\|\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0\|^2\}. \quad (\text{S5.259})$$

Combining (S5.257), (S5.258), and (S5.259) we deduce that

$$2\Sigma_{\mathbf{X}_{-1}}(\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0) = T_1 + T_2 + o_p\{m^{-1/2}n^{-1/2} + \|\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0\|^2\}. \quad (\text{S5.260})$$

Observe that  $E(T_1) = E(T_2) = 0$ . The variance of  $T_1$  is

$$\begin{aligned}
& E(T_1 T_1^T) \\
&= \left[ \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \{ \mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} - U_i) - \mathbf{X}_{ij,-1} \} - \frac{\boldsymbol{\mu}_{\mathbf{X}_{-1}}}{m} \sum_{i=1}^m S_1 \right] \\
&\quad \times \left[ \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \{ \mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} - U_i) - \mathbf{X}_{ij,-1} \} - \frac{\boldsymbol{\mu}_{\mathbf{X}_{-1}}}{m} \sum_{i=1}^m S_1 \right]^T \\
&= \left[ \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n [ \{ \mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} - U_i) - \mathbf{X}_{ij,-1} \} \right. \\
&\quad \left. - \frac{\boldsymbol{\mu}_{\mathbf{X}_{-1}}}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} Y_{ij} \exp(-\beta_0^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) - \boldsymbol{\mu}_{\mathbf{X}_{-1}} ] \right] \\
&\quad \times \left[ \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n [ \{ \mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} - U_i) - \mathbf{X}_{ij,-1} \} \right. \\
&\quad \left. - \frac{\boldsymbol{\mu}_{\mathbf{X}_{-1}}}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) - \boldsymbol{\mu}_{\mathbf{X}_{-1}} ] \right]^T \\
&= T_{11} + T_{12} + T_{13}, \tag{S5.261}
\end{aligned}$$

where

$$\begin{aligned}
T_{11} &= \frac{1}{mn} E \left[ \{ Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} - U_i) - 1 \}^2 \mathbf{X}_{ij,-1} \mathbf{X}_{ij,-1}^T \right. \\
&\quad + \{ \frac{1}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) - 1 \}^2 \boldsymbol{\mu}_{\mathbf{X}_{-1}} \boldsymbol{\mu}_{\mathbf{X}_{-1}}^T \\
&\quad - 2 \{ Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} - U_i) - 1 \} \\
&\quad \left. \times \{ \frac{1}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) - 1 \} \mathbf{X}_{ij,-1} \boldsymbol{\mu}_{\mathbf{X}_{-1}}^T \right] \\
&= \frac{1}{mn} [\exp\{(\sigma_v^2)^0\} - 1] \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} + \frac{\exp\{(\sigma_v^2)^0\}}{mn\alpha} \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} \tag{S5.262}
\end{aligned}$$

$$\begin{aligned}
 T_{12} &= \frac{1}{m^2 n^2} \sum_{i=1}^m \sum_{j=1}^n \sum_{l \neq j}^n E[\{\mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} - U_i) - \mathbf{X}_{ij,-1}\} \\
 &\quad - \frac{\boldsymbol{\mu}_{\mathbf{X}_{-1}}}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) + \boldsymbol{\mu}_{\mathbf{X}_{-1}}\} \\
 &\quad \times \{\mathbf{X}_{il,-1} Y_{il} \exp(-\mathbf{X}_{il}^T \boldsymbol{\beta}^{r0} - U_i) - \mathbf{X}_{il,-1} \\
 &\quad - \frac{\boldsymbol{\mu}_{\mathbf{X}_{-1}}}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} Y_{il} \exp(-\beta_1^{r0} - \mathbf{X}_{il,-1}^T \boldsymbol{\beta}_{-1} - U_i) + \boldsymbol{\mu}_{\mathbf{X}_{-1}}\}] \\
 &= 0, \tag{S5.263}
 \end{aligned}$$

$$\begin{aligned}
 T_{13} &= \frac{1}{m^2 n^2} \sum_{i=1}^m \sum_{k \neq i}^m \sum_{j=1}^n E[\{\mathbf{X}_{ij,-1} Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} - U_i) - \mathbf{X}_{ij,-1} \\
 &\quad - \frac{\boldsymbol{\mu}_{\mathbf{X}_{-1}}}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) + \boldsymbol{\mu}_{\mathbf{X}_{-1}}\} \\
 &\quad \times \{\mathbf{X}_{kj,-1} Y_{kj} \exp(-\mathbf{X}_{kj}^T \boldsymbol{\beta}^{r0} - U_k) - \mathbf{X}_{kj,-1}\} \\
 &\quad - \frac{\boldsymbol{\mu}_{\mathbf{X}_{-1}}}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} Y_{kj} \exp(-\beta_1^{r0} - \mathbf{X}_{kj,-1}^T \boldsymbol{\beta}_{-1} - U_k) + \boldsymbol{\mu}_{\mathbf{X}_{-1}}\}] \\
 &= 0. \tag{S5.264}
 \end{aligned}$$

Combining (S5.261)-(S5.264) we deduce that

$$E(T_1 T_1^T) = \frac{\exp\{(\sigma_v^2)^0\} - 1}{mn} \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} + \frac{\exp\{(\sigma_v^2)^0\}}{mn\alpha} \boldsymbol{\Sigma}_{\mathbf{X}_{-1}}. \tag{S5.265}$$

The variance of  $T_2$  can be calculated analogously,

$$E(T_2 T_2^T) = \frac{\exp\{(\sigma_u^2)^0\} - 1}{mn} \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} + \frac{\exp\{(\sigma_u^2)^0\}}{mn\alpha} \boldsymbol{\Sigma}_{\mathbf{X}_{-1}}. \tag{S5.266}$$

Furthermore, we have

$$T_1 = O_p\{(mn)^{-1/2}\} \text{ and } T_2 = O_p\{(mn)^{-1/2}\}.$$

By (S4.231), (S4.232), and (S5.256),

$$\begin{aligned}\beta_1^r - \beta_1^{r0} &= \phi_1^T(\mathbf{0})(\beta_{-1}^0 - \beta_{-1}) + O_p\{(mn)^{-1/2}\} \\ &\quad + \frac{1}{m} \sum_{i=1}^m \{U_i + \Delta_{i,1} - \hat{\mu}_{u_i} + \hat{\lambda}_{u_i}/2\},\end{aligned}\quad (\text{S5.267})$$

$$\begin{aligned}\beta_1^c - \beta_1^{c0} &= \phi_1^T(\mathbf{0})(\beta_{-1}^0 - \beta_{-1}) + O_p\{(mn)^{-1/2}\} \\ &\quad + \frac{1}{n} \sum_{j=1}^n \{V_j + \Delta'_{j,1} - \hat{\mu}_{v_j} + \hat{\lambda}_{v_j}/2\}.\end{aligned}\quad (\text{S5.268})$$

### S5.2 Final approximations to $\sigma_u^2 - (\sigma_u^2)^0$ and $\sigma_v^2 - (\sigma_v^2)^0$

Therefore, squaring both sides of (S4.237) and adding  $i$  from 1 to  $m$  we have

$$\frac{1}{m} \sum_{i=1}^m \hat{\mu}_{u_i}^2 = \frac{1}{m} \sum_{i=1}^m (U_i + \Delta_{i,1} - \bar{U} - \bar{\Delta}_{i,1})^2 + O_p(n^{-1}).$$

Combining (S4.183), (S4.208), (S4.227), and (S4.237) we have

$$\begin{aligned}\hat{\sigma}_u^2 &= \frac{1}{m} \sum_{i=1}^m (U_i + \Delta_{i,1} - \bar{U} - \bar{\Delta}_{i,1})^2 + O_p\{n^{-1} + (mn)^{-1/2}\} \\ &= \frac{1}{m} \sum_{i=1}^m U_i^2 + \frac{1}{m} \sum_{i=1}^m \Delta_{i,1}^2 + \frac{2}{m} \sum_{i=1}^m U_i \Delta_{i,1} + O_p(m^{-1} + n^{-1}) \\ &= \frac{1}{m} \sum_{i=1}^m U_i^2 + O_p\{(m^{-1/2} + n^{-1/2})^2\}.\end{aligned}$$

Therefore,

$$\hat{\sigma}_u^2 - (\sigma_u^2)^0 = \frac{1}{m} \sum_{i=1}^m \{U_i^2 - (\sigma_u^2)^0\} + O_p\{(m^{-1/2} + n^{-1/2})^2\},$$

which implies the asymptotic normality result of  $\widehat{\underline{\sigma}}_u^2$  in Theorem 2. The expression of  $\widehat{\underline{\sigma}}_v^2$  can be derived analogously:

$$\widehat{\underline{\sigma}}_v^2 = \frac{1}{n} \sum_{j=1}^n (V_j - \Delta'_{j,1} - \bar{V} - \bar{\Delta}'_{j,1})^2 + O_p\{(m^{-1/2} + n^{-1/2})^2\},$$

and

$$\widehat{\underline{\sigma}}_v^2 - (\sigma_v^2)^0 = \frac{1}{n} \sum_{j=1}^n \{V_j^2 - (\sigma_v^2)^0\} + O_p\{(m^{-1/2} + n^{-1/2})^2\},$$

which implies the asymptotic normality result of  $\widehat{\underline{\sigma}}_v^2$  in Theorem 2.

### S5.3 Final approximations to $\widehat{\underline{\beta}}_1 - \beta_1^0$ and $\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0$

Based on (S5.260), we have

$$\begin{aligned} \widehat{\underline{\beta}}_{-1} - \beta_{-1}^0 &= \frac{1}{2} \Sigma_{\mathbf{X}_{-1}}^{-1} T_1 + \frac{1}{2} \Sigma_{\mathbf{X}_{-1}}^{-1} T_2 \\ &\quad + o_p\{(mn)^{-1/2} + \|\widehat{\underline{\beta}}_{-1} - \beta_{-1}^0\|^2\}. \end{aligned} \quad (\text{S5.269})$$

Using (S5.265), (S5.266), and the covariance of  $T_1$  and  $T_2$ ,

$$\begin{aligned}
& \text{cov}(T_1, T_2) \\
&= E \left( \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \left[ \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{r0} - U_i) - 1\} \mathbf{X}_{ij,-1} \right. \right. \\
&\quad \left. \left. - \left\{ \frac{1}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} Y_{ij} \exp(-\beta_1^{r0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - U_i) - 1 \right\} \boldsymbol{\mu}_{\mathbf{X}_{-1}} \right] \right. \\
&\quad \left. \times \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \left[ \{Y_{ij} \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta}^{c0} - V_j) - 1\} \mathbf{X}_{ij,-1} \right. \right. \\
&\quad \left. \left. - \left\{ \frac{1}{\phi(\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})} Y_{ij} \exp(-\beta_1^{c0} - \mathbf{X}_{ij,-1}^T \boldsymbol{\beta}_{-1} - V_j) - 1 \right\} \boldsymbol{\mu}_{\mathbf{X}_{-1}} \right] \right)^T \\
&= \frac{1}{mn} \frac{1}{\alpha} [\boldsymbol{\mu}_{\mathbf{X}_{-1}} \boldsymbol{\mu}_{\mathbf{X}_{-1}}^T + \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} - 2\{\boldsymbol{\mu}_{\mathbf{X}_{-1}} \boldsymbol{\mu}_{\mathbf{X}_{-1}}^T + o_p(1)\} \\
&\quad + \boldsymbol{\mu}_{\mathbf{X}_{-1}} \boldsymbol{\mu}_{\mathbf{X}_{-1}}^T \{1 + \boldsymbol{\mu}_{\mathbf{X}_{-1}}^T (\boldsymbol{\beta}_{-1}^0 - \boldsymbol{\beta}_{-1})\}] \\
&= \frac{1}{mn} \frac{1}{\alpha} \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} + o_p\{(mn)^{-1}\},
\end{aligned}$$

Since

$$\begin{aligned}
& \text{Var}(T_1 + T_2) \\
&= \text{Var}(T_1) + \text{Var}(T_2) + 2\text{cov}(T_1, T_2) \\
&= \frac{1 + \alpha}{mn\alpha} \exp\{(\sigma_v^2)^0\} \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} - \frac{1}{mn} \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} \\
&\quad + \frac{1 + \alpha}{mn\alpha} \exp\{(\sigma_u^2)^0\} \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} - \frac{1}{mn} \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} + 2 \frac{1}{mn\alpha} \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} \\
&= \frac{\exp\{(\sigma_u^2)^0\} + \exp\{(\sigma_v^2)^0\} - 2}{mn} \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} \\
&\quad + \frac{\exp\{(\sigma_u^2)^0\} + \exp\{(\sigma_v^2)^0\} + 2}{mn\alpha} \boldsymbol{\Sigma}_{\mathbf{X}_{-1}} \tag{S5.270}
\end{aligned}$$

we can define a covariance matrix  $\tilde{\Sigma}$  by

$$\begin{aligned}\tilde{\Sigma} &= \frac{1}{4}\Sigma_{\mathbf{X}_{-1}}^{-1}Var(T_1 + T_2)\Sigma_{\mathbf{X}_{-1}}^{-1} \\ &= \left( \frac{1}{4mn}[\exp\{(\sigma_u^2)^0\} + \exp\{(\sigma_v^2)^0\} - 2] \right. \\ &\quad \left. + \frac{1}{4mn\alpha}[\exp\{(\sigma_u^2)^0\} + \exp\{(\sigma_v^2)^0\} + 2] \right) \Sigma_{\mathbf{X}_{-1}}^{-1}. \quad (\text{S5.271})\end{aligned}$$

Combining (S5.269), (S5.271), and the multivariate central limit theorem

we have

$$\sqrt{mn}(\hat{\underline{\beta}}_{-1} - \beta_{-1}^0) \rightarrow N(0, \tilde{\Sigma})$$

in distribution, as  $m, n \rightarrow \infty$ . By (S5.267), (S5.268), and (S5.269), we

have

$$\begin{aligned}& \hat{\underline{\beta}}_{-1} - \beta_{-1}^0 \tag{S5.272} \\ &= -(\hat{\underline{\beta}}_{-1} - \beta_{-1}^0)\mu_X + \frac{1}{2m} \sum_{i=1}^m (U_i + \Delta_{i,1}) + \frac{1}{2n} \sum_{j=1}^n (V_j + \Delta'_{j,1}) \\ &\quad - \frac{1}{4} \{ \hat{\underline{\sigma}}_u^2 - (\sigma_u^2)^0 + \hat{\underline{\sigma}}_v^2 - (\sigma_v^2)^0 \} + O_p\{(m^{-1/2} + n^{-1/2})^2\} \\ &= \frac{1}{2}\bar{V} + \frac{1}{2}\bar{\Delta}_{i,1} - \frac{1}{4n} \sum_{j=1}^n \{V_j^2 - (\sigma_v^2)^0\} \\ &\quad + \frac{1}{2}\bar{U} + \frac{1}{2}\bar{\Delta}'_{j,1} - \frac{1}{4m} \sum_{i=1}^m \{U_i^2 - (\sigma_u^2)^0\} + O_p\{(m^{-1/2} + n^{-1/2})^2\} \\ &:= SS_1 + SS_2 + SS_3 + SS_4 + SS_5 + SS_6 + O_p\{(m^{-1/2} + n^{-1/2})^2\},\end{aligned}$$

where

$$\begin{aligned}
SS_1 &= \frac{1}{2}\bar{V}, \\
SS_2 &= \frac{1}{2}\bar{\Delta}_{i,1}, \\
SS_3 &= -\frac{1}{4n}\sum_{j=1}^n\{V_j^2 - (\sigma_v^2)^0\}, \\
SS_4 &= \frac{1}{2}\bar{U}, \\
SS_5 &= \frac{1}{2}\bar{\Delta}'_{j,1}, \\
SS_6 &= -\frac{1}{4m}\sum_{i=1}^m\{U_i^2 - (\sigma_u^2)^0\}.
\end{aligned}$$

By the requirements of the multivariate central limit theorem, we need to check the boundedness of covariances of  $(SS_1, SS_2, SS_3, SS_4, SS_5, SS_6)$ .

The diagonal elements can be calculated as follows,

$$\text{var}(SS_1) = \frac{1}{4n}(\sigma_v^2)^0, \quad (\text{S5.273})$$

$$\text{var}(SS_2) = \frac{1}{4n}[\exp\{(\sigma_v^2)^0\} - 1], \quad (\text{S5.274})$$

$$\text{var}(SS_3) = \frac{1}{8n}\{(\sigma_v^2)^0\}^2, \quad (\text{S5.275})$$

$$\text{var}(SS_4) = \frac{1}{4m}(\sigma_u^2)^0, \quad (\text{S5.276})$$

$$\text{var}(SS_5) = \frac{1}{4m}[\exp\{(\sigma_u^2)^0\} - 1], \quad (\text{S5.277})$$

$$\text{var}(SS_6) = \frac{1}{8m}\{(\sigma_u^2)^0\}^2. \quad (\text{S5.278})$$

The covariances can be computed as follows,

$$\text{cov}(SS_1, SS_2) = \frac{1}{4n}(\sigma_v^2)^0, \quad (\text{S5.279})$$

$$\text{cov}(SS_1, SS_3) = 0, \quad (\text{S5.280})$$

$$\text{cov}(SS_2, SS_3) = -\frac{1}{8m}(\sigma_u^4)^0, \quad (\text{S5.281})$$

$$\text{cov}(SS_4, SS_5) = \frac{1}{4m}(\sigma_u^2)^0, \quad (\text{S5.282})$$

$$\text{cov}(SS_4, SS_6) = 0, \quad (\text{S5.283})$$

$$\text{cov}(SS_5, SS_6) = -\frac{1}{8n}\{(\sigma_u^2)^0\}^2 \quad (\text{S5.284})$$

For simplicity, combining (S5.273)-(S5.284) we define two matrices by

$$\mathbf{\Gamma}_4 = \frac{1}{8} \begin{pmatrix} 2(\sigma_u^2)^0 & 2(\sigma_u^2)^0 & 0 \\ 2(\sigma_u^2)^0 & 2[\exp\{(\sigma_u^2)^0\} - 1] & -\{(\sigma_u^2)^0\}^2 \\ 0 & -\{(\sigma_u^2)^0\}^2 & \{(\sigma_u^2)^0\}^2 \end{pmatrix}. \quad (\text{S5.285})$$

and

$$\mathbf{\Gamma}_5 = \frac{1}{8} \begin{pmatrix} 2(\sigma_v^2)^0 & 2(\sigma_v^2)^0 & 0 \\ 2(\sigma_v^2)^0 & 2[\exp\{(\sigma_v^2)^0\} - 1] & -\{(\sigma_v^2)^0\}^2 \\ 0 & -\{(\sigma_v^2)^0\}^2 & \{(\sigma_v^2)^0\}^2 \end{pmatrix}, \quad (\text{S5.286})$$

Combining (S5.272), (S5.285), (S5.286), and the multivariate central limit theorem we deduce that

$$\begin{aligned} & (\sqrt{m}(SS_4, SS_5, SS_6), \sqrt{n}(SS_1, SS_2, SS_3))^T \\ \rightarrow & N \left( \begin{pmatrix} \mathbf{0}_3 \\ \mathbf{0}_3 \end{pmatrix}, \begin{pmatrix} \mathbf{\Gamma}_4 & 0 \\ 0 & \mathbf{\Gamma}_5 \end{pmatrix} \right), \end{aligned} \quad (\text{S5.287})$$

as  $m, n \rightarrow \infty$ . By results (S5.272), (S5.287), we obtain

$$\widehat{\underline{\beta}}_1 - \beta_1^0 = m^{-1/2} \mathbf{1}_3^T Z_7 + n^{-1/2} \mathbf{1}_3^T Z_8 + o_p(m^{-1/2} + n^{-1/2}),$$

where  $Z_7$  and  $Z_8$  are normal distributions with mean zeros and variances  $\mathbf{\Gamma}_4$  and  $\mathbf{\Gamma}_5$ , respectively.

## S6 Additional simulation results

### S6.1 Simulations for the Gamma regression model with $\delta = 1$

We conduct the simulation studies to assess the performance of the Gamma regression models with crossed random effects as specified in equation (S1.2). Except the case in the manuscript, we also consider another case, independently generate  $\mathbf{X}_{ij,-1}$  from  $N(0, I_{8 \times 8})$  for  $i = 1, \dots, m$  and  $j = 1, \dots, n$ , where  $I_{8 \times 8}$  is an identity matrix. We set  $\boldsymbol{\beta}^0 = (-2, 1, 0.5, 1, -1, 0.5, 1, -1, 0.5, 0.8, -0.4, 0.1)$ ,  $(\sigma_u)^0 = 0.5$ , and  $(\sigma_v)^0 = 0.5$ . The additional shape parameter is set as  $\alpha = 0.8$ . We consider nine different scenarios:  $(m, n) \in \{(18, 12), (20, 20), (30, 30), (50, 50), (80, 80), (100, 100), (150, 150), (200, 200), (300, 300)\}$ , which imply the nine increasing sample sizes  $m * n \in \{216, 400, 900, 2500, 6400, 10000, 22500, 40000, 90000\}$ . We report the results based on 500 Monte Carlo studies in Figures S1, and S2.

Theorem 2 reveals that  $\widehat{\underline{\boldsymbol{\beta}}}$ ,  $\widehat{\underline{\sigma}}_u$ , and  $\widehat{\underline{\sigma}}_v$  are each asymptotically normal with means corresponding to the true parameter values. Based on Theorem 2, the approximate 95% confidence intervals for  $\beta_1, \beta_j, j = 2, \dots, p, \sigma_u^0$ , and  $\sigma_v^0$  are  $\widehat{\underline{\beta}}_1 \pm 1.96 * \text{var}(\widehat{\underline{\beta}}_1)$ ,  $\widehat{\underline{\beta}}_j \pm 1.96 * \text{var}(\widehat{\underline{\beta}}_j), j = 2, \dots, p$ ,  $\widehat{\underline{\sigma}}_u \pm 1.96 * \text{var}(\widehat{\underline{\sigma}}_u)$ ,  $\widehat{\underline{\sigma}}_v \pm 1.96 * \text{var}(\widehat{\underline{\sigma}}_v)$ . These confidence intervals are asymptotically valid, as they rely on studentization using consistent estimators for unknown

parameters. We also report the coverage percentages for the 95% confidence intervals in Figure S3.

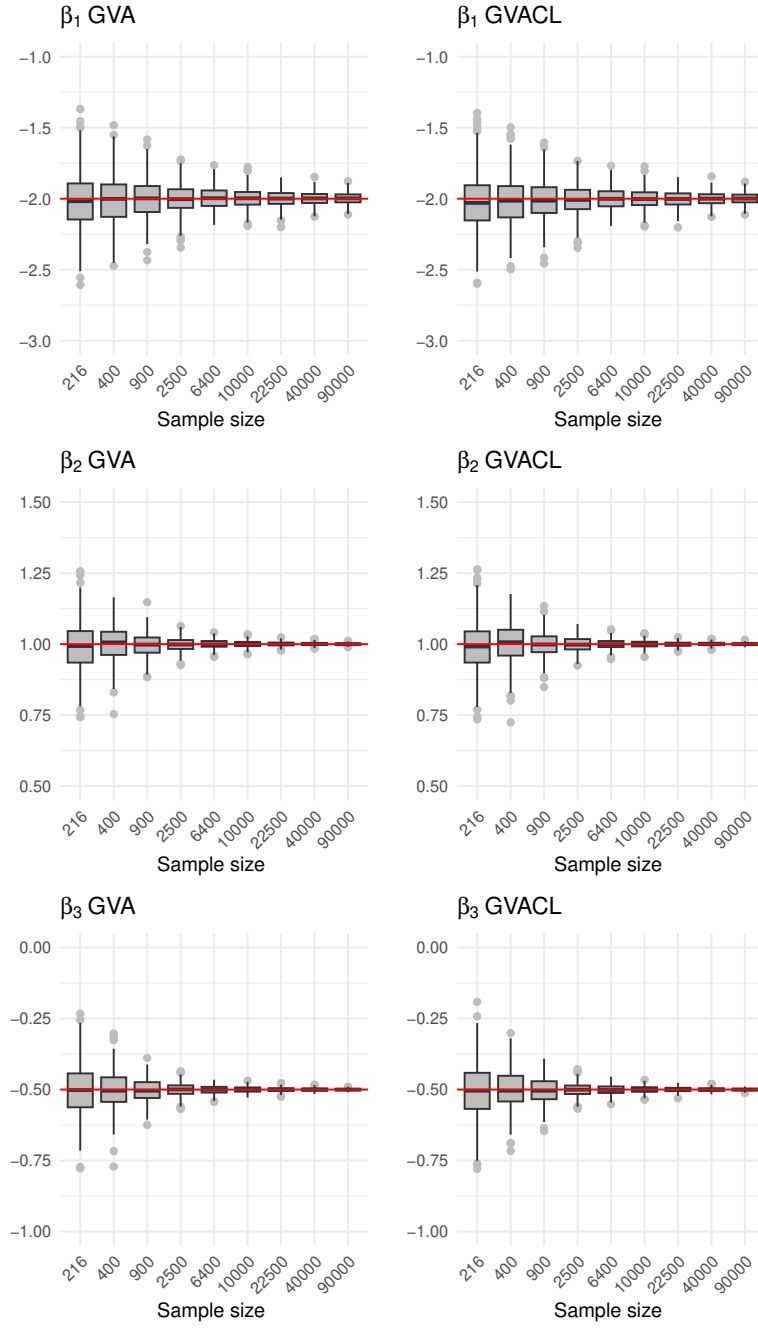


Figure S1: Boxplots of  $\beta_1, \beta_2$ , and  $\beta_3$  estimates obtained by GVA and GVACL for the Gamma regression model with crossed random effects based on 500 datasets. Red horizontal reference lines represent the true parameter values. The ratio  $\log m / \log n$  converges to 1.

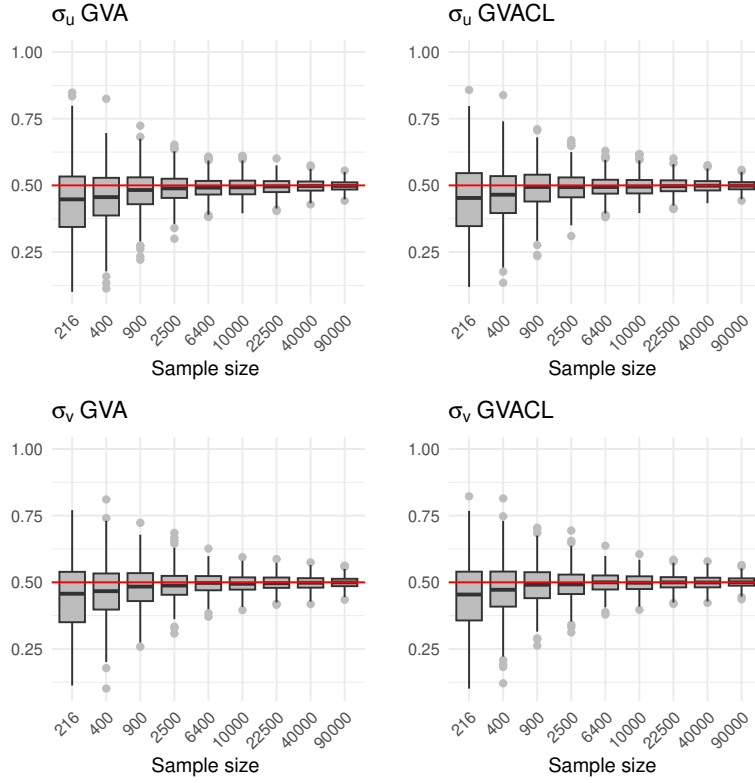


Figure S2: Boxplots of  $\sigma_u$  and  $\sigma_v$  estimates obtained by GVA and GVACL for the Gamma regression model with crossed random effects based on 500 datasets. Red horizontal reference lines represent the true parameter values. The ratio  $\log m / \log n$  converges to 1.

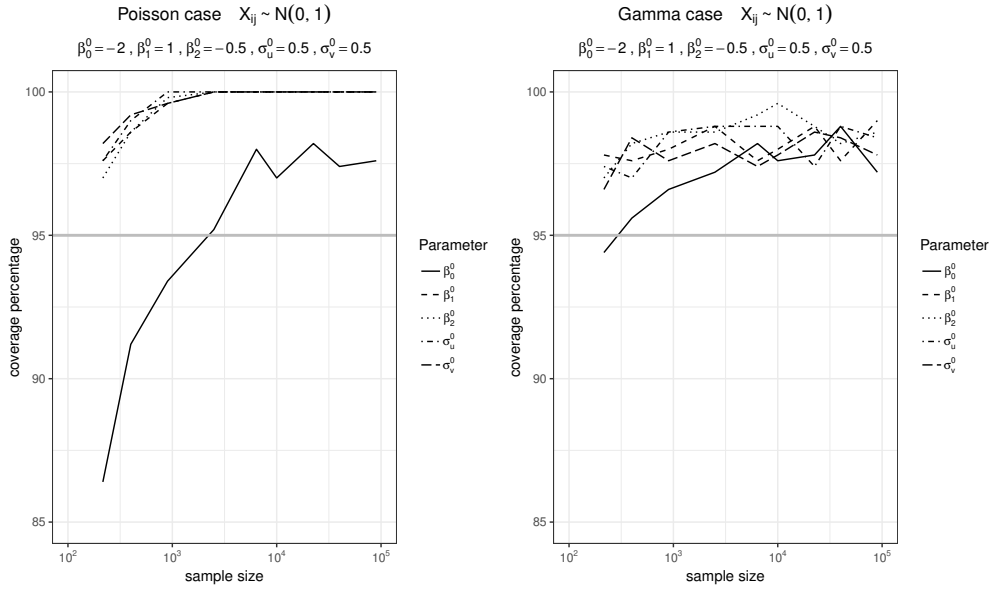


Figure S3: The coverage percentage of the 95% GVACL confidence intervals for the parameters in Poisson and Gamma regression models with crossed random effects based on 500 replications. The 95% percentage is shown as a thick grey horizontal line. The ratio  $\log m / \log n$  converges to 1.

### S6.2 Simulations for the logistic regression model with $\delta = 1$

We also consider simulation studies for the following logistic regression model with crossed random effects,

$$Y_{ij} = 1 \mid \mathbf{X}_{ij}, U_i, V_j \sim \text{Bernoulli}[1/\{1 + \exp(-\mathbf{X}_{ij}^T \boldsymbol{\beta} - U_i - V_j)\}],$$

$$U_i \sim N(0, (\sigma_u^2)^0), V_j \sim N(0, (\sigma_v^2)^0), U_i \text{ and } V_j \text{ are independent.}$$

The variational lower bound of the CL for the logistic regression model with crossed random effects is

$$\begin{aligned} & \underline{\text{cl}}(\boldsymbol{\Psi}^{rc}, \boldsymbol{\xi}) \\ = & \sum_{i=1}^m \sum_{j=1}^n \{Y_{ij}(\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i}) - \int \log(1 + \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + U_i)) \phi(u_i) du_i\} \\ & - \frac{m}{2} \log(\sigma_u^2) - \frac{1}{2\sigma_u^2} \sum_{i=1}^m (\mu_{u_i}^2 + \lambda_{u_i}) + \frac{1}{2} \log \lambda_{u_i} \\ & + \sum_{j=1}^n \sum_{i=1}^m [Y_{ij}(\mathbf{X}_{ij}^T \boldsymbol{\beta}^c + \mu_{v_j}) - \int \log\{1 + \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^c + V_j)\} \phi(v_j) dv_j] \\ & - \frac{n}{2} \log(\sigma_v^2) - \frac{1}{2\sigma_v^2} \sum_{j=1}^n (\mu_{v_j}^2 + \lambda_{v_j}) + \frac{1}{2} \log \lambda_{v_j} \\ \geq & \sum_{i=1}^m \sum_{j=1}^n \{Y_{ij}(\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_{u_i}) - \log(1 + \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^r + \mu_i + \lambda_{u_i}/2))\} \\ & - \frac{m}{2} \log(\sigma_u^2) - \frac{1}{2\sigma_u^2} \sum_{i=1}^m (\mu_{u_i}^2 + \lambda_{u_i}) + \frac{1}{2} \log \lambda_{u_i} \\ & + \sum_{j=1}^n \sum_{i=1}^m [Y_{ij}(\mathbf{X}_{ij}^T \boldsymbol{\beta}^c + \mu_{v_j}) - \log\{1 + \exp(\mathbf{X}_{ij}^T \boldsymbol{\beta}^c + \mu_{v_j} + \lambda_{v_j}/2)\}] \\ & - \frac{n}{2} \log(\sigma_v^2) - \frac{1}{2\sigma_v^2} \sum_{j=1}^n (\mu_{v_j}^2 + \lambda_{v_j}) + \frac{1}{2} \log \lambda_{v_j} := \underline{\text{cl}}(\boldsymbol{\Psi}^{rc}, \boldsymbol{\xi}). \quad (\text{S6.288}) \end{aligned}$$

We consider four scenarios:  $(m, n) \in \{(200, 200), (250, 250), (300, 300), (400, 400)\}$ , and set the other parameters as the same as the Poisson and Gamma regression models described in §S6.1. The simulation results of the logistic regression model with crossed random effects based on 500 Monte Carlo studies are reported in Figures S4, S5, and S6. We found that the computational time of the proposed method is much smaller than for the Laplace approximation in the package `glmmTMB` and a GVA applied to the full log-likelihood function.

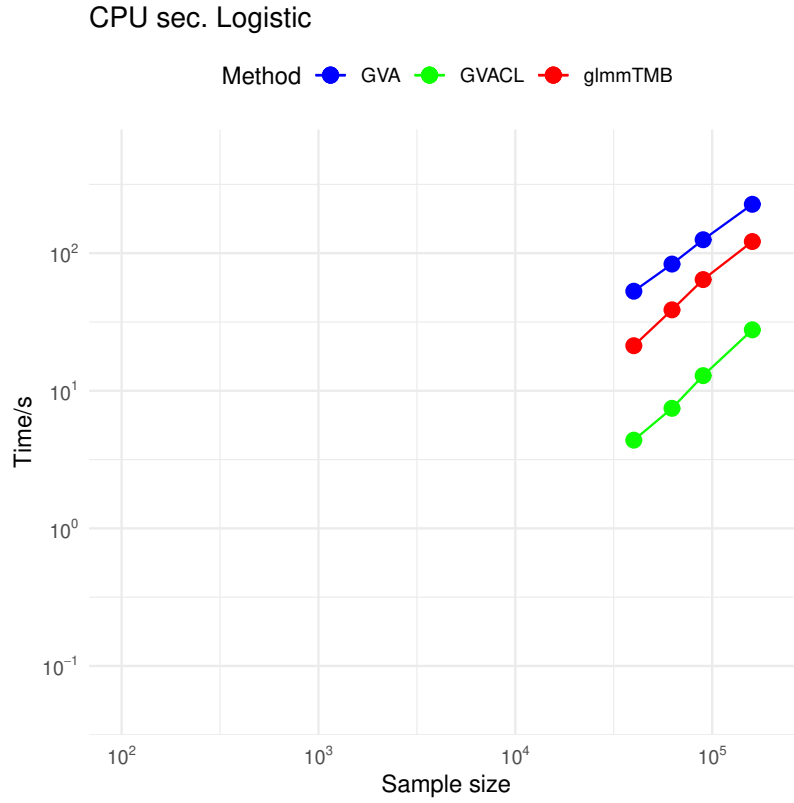


Figure S4: Average time of each simulation in seconds versus sample size  $m * n$  under four different scenarios for the logistic regression model with crossed random effects. The ratio  $\log m / \log n$  converges to 1.

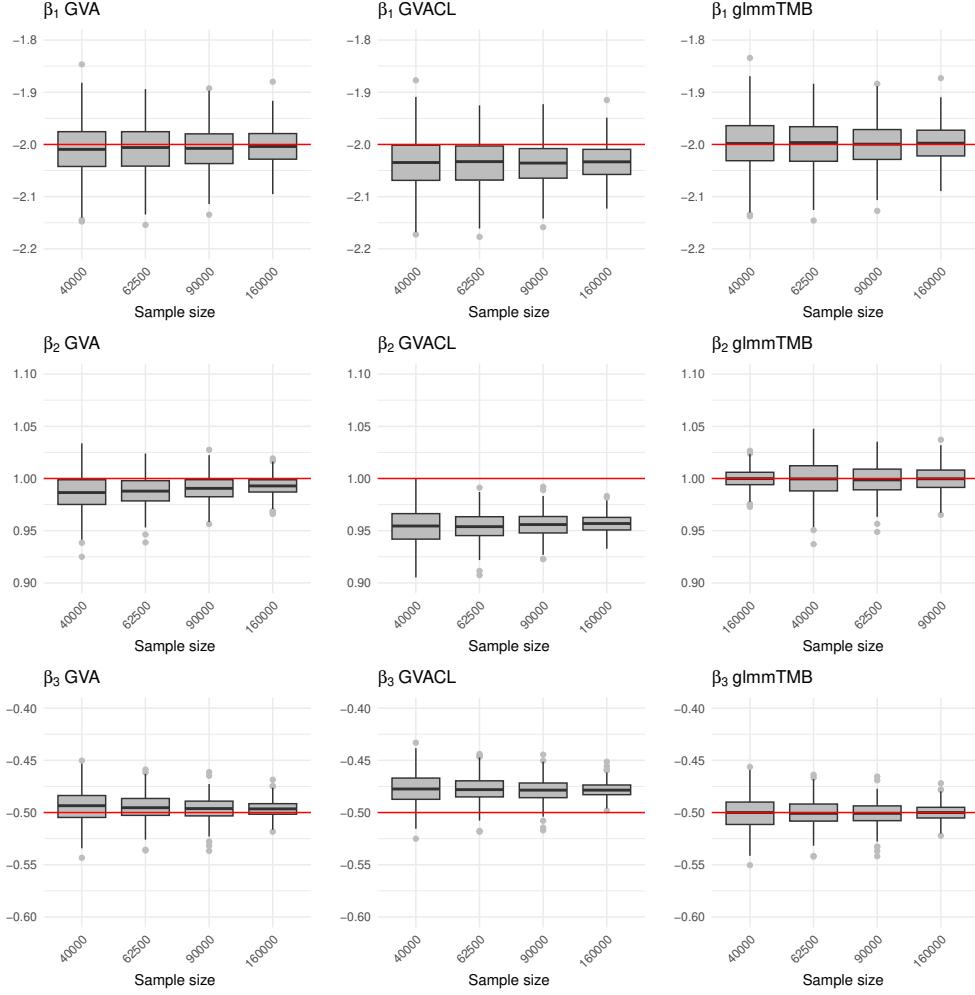


Figure S5: Boxplots of  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$  estimates obtained by GVA, GVACL, and glmmTMB for the logistic regression model with crossed random effects based on 500 datasets. Red horizontal reference lines represent the true parameter values. The ratio  $\log m / \log n$  converges to 1.

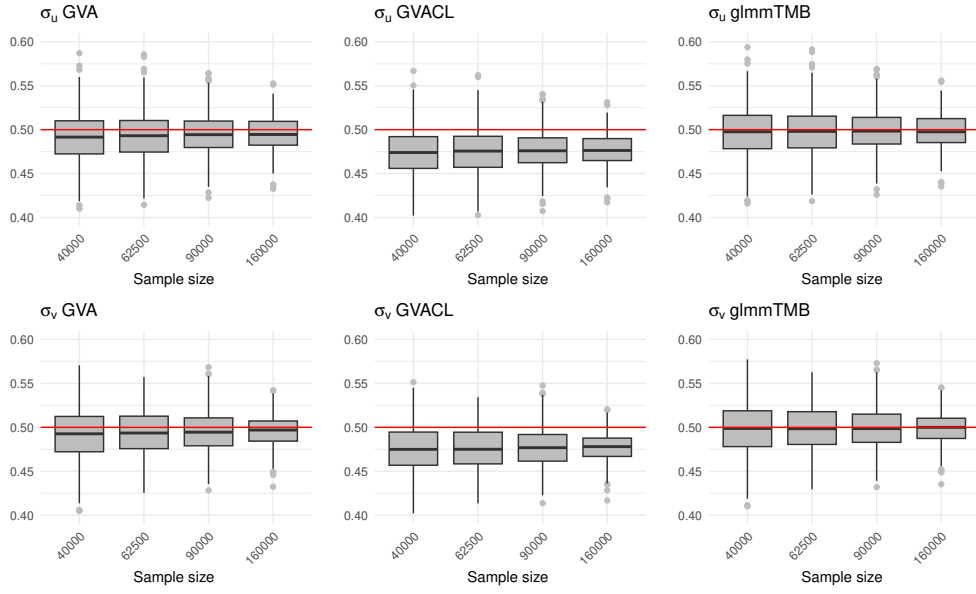


Figure S6: Boxplots of  $\sigma_u$  and  $\sigma_v$  estimates obtained by GVA, GVACL, and `glmmTMB` for the logistic regression model with crossed random effects based on 500 datasets. Red horizontal reference lines represent the true parameter values. The ratio  $\log m / \log n$  converges to 1.

### S6.3 Simulations for Poisson, Gamma, and logistic regression models with $\delta = 1.1$

We also conduct the simulation studies to assess the performance of the Poisson, Gamma, and logistic regression models with crossed random effects. Except the case in the manuscript, we also consider another case, independently generate  $\mathbf{X}_{ij,-1}$  from  $N(0, I_{8 \times 8})$  for  $i = 1, \dots, m$  and  $j = 1, \dots, n$ , where  $I_{8 \times 8}$  is an identity matrix. We set  $\beta^0 = (-2, 1, 0.5, 1, -1, 0.5, 0.8, -0.4, 0.1)$ ,  $(\sigma_u)^0 = 0.5$ , and  $(\sigma_v)^0 = 0.5$ . The additional shape parameter is set as  $\alpha = 0.8$ . For Poisson and Gamma cases, we consider nine different scenarios :  $(m, n) \in \{(18, 14), (20, 15), (30, 22), (50, 35), (80, 54), (100, 66), (150, 95), (200, 124), (300, 179)\}$ , which imply the nine increasing sample sizes  $m * n \in \{252, 300, 660, 1750, 4320, 6600, 14250, 24800, 53700\}$ . Most Monte Carlo simulations of GVA to logistic case fails to converge when the sample size is small. Hence we consider four different scenarios:  $(m, n) \in \{(200, 124), (250, 151), (300, 179), (400, 232)\}$ . We report the results based on 500 Monte Carlo studies in Figures S8-S15.

## S6. ADDITIONAL SIMULATION RESULTS

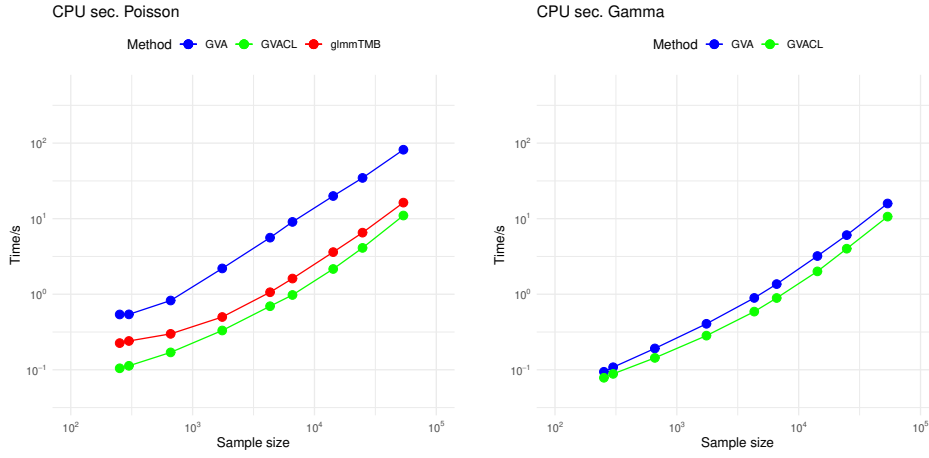


Figure S7: Average time of each simulation in seconds versus sample size  $m * n$  under different scenarios for the Poisson and Gamma regression models with crossed random effects. The ratio  $\log m / \log n$  converges to 1.1.

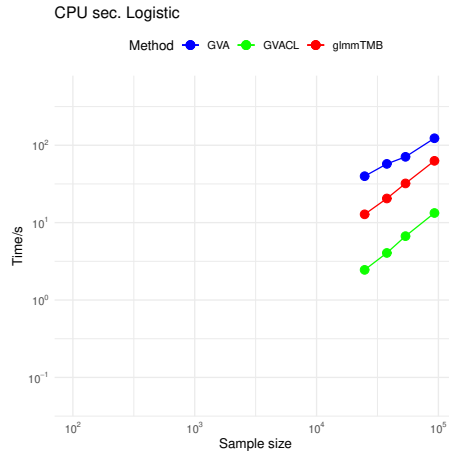


Figure S8: Average time of each simulation in seconds versus sample size  $m * n$  under different scenarios for the logistic regression models with crossed random effects. The ratio  $\log m / \log n$  converges to 1.1.

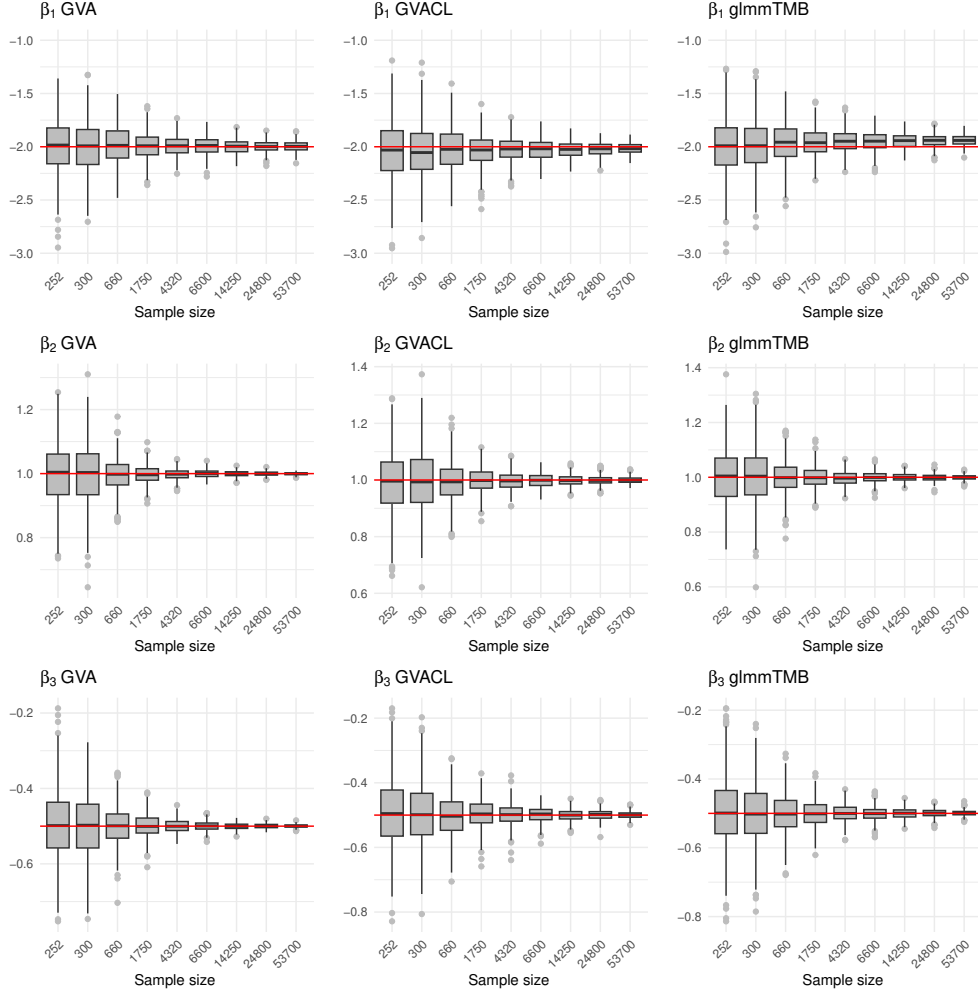


Figure S9: Boxplots of  $\beta_1, \beta_2$ , and  $\beta_3$  estimates obtained by GVA and GVACL for the Poisson regression model with crossed random effects based on 500 datasets. Red horizontal reference lines represent the true parameter values. The ratio  $\log m / \log n$  converges to 1.1.

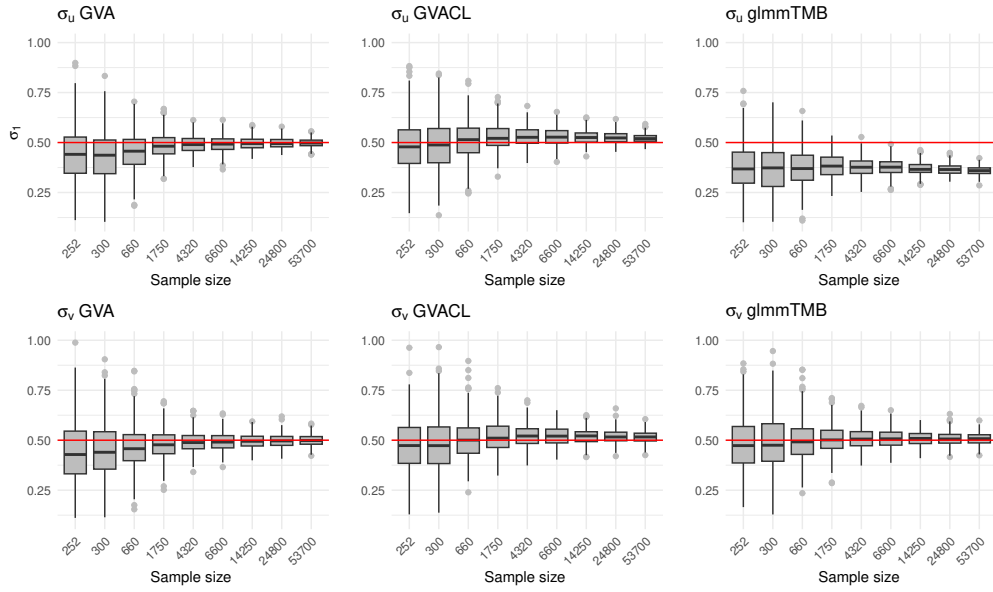


Figure S10: Boxplots of  $\sigma_u$  and  $\sigma_v$  estimates obtained by GVA and GVACL for the Poisson regression model with crossed random effects based on 500 datasets. Red horizontal reference lines represent the true parameter values. The ratio  $\log m / \log n$  converges to 1.1.

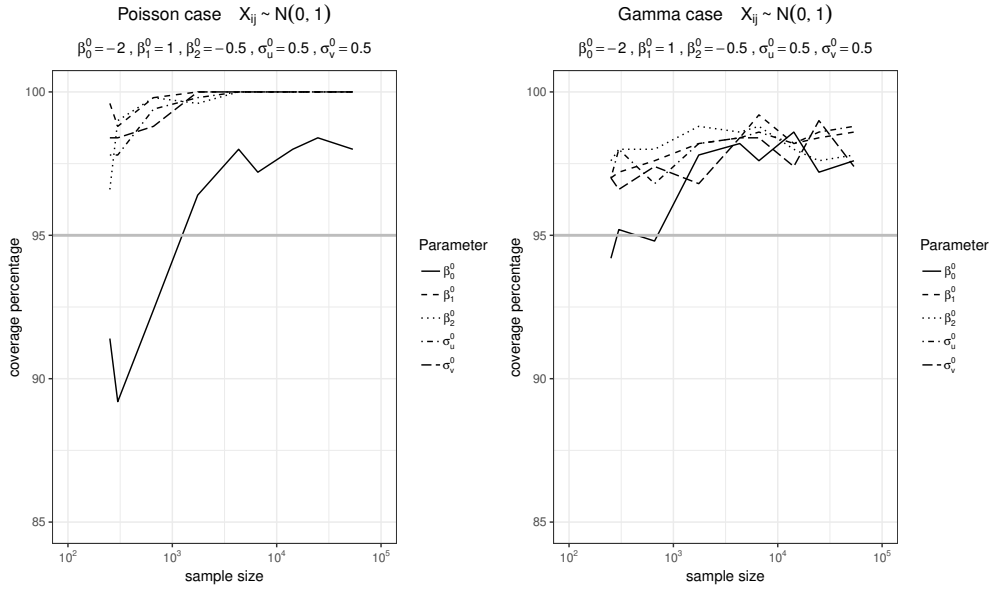


Figure S11: The coverage percentage of the 95% GVACL confidence intervals for the parameters in Poisson and Gamma regression models with crossed random effects based on 500 replications. The 95% percentage is shown as a thick grey horizontal line. The ratio  $\log m / \log n$  converges to 1.1.

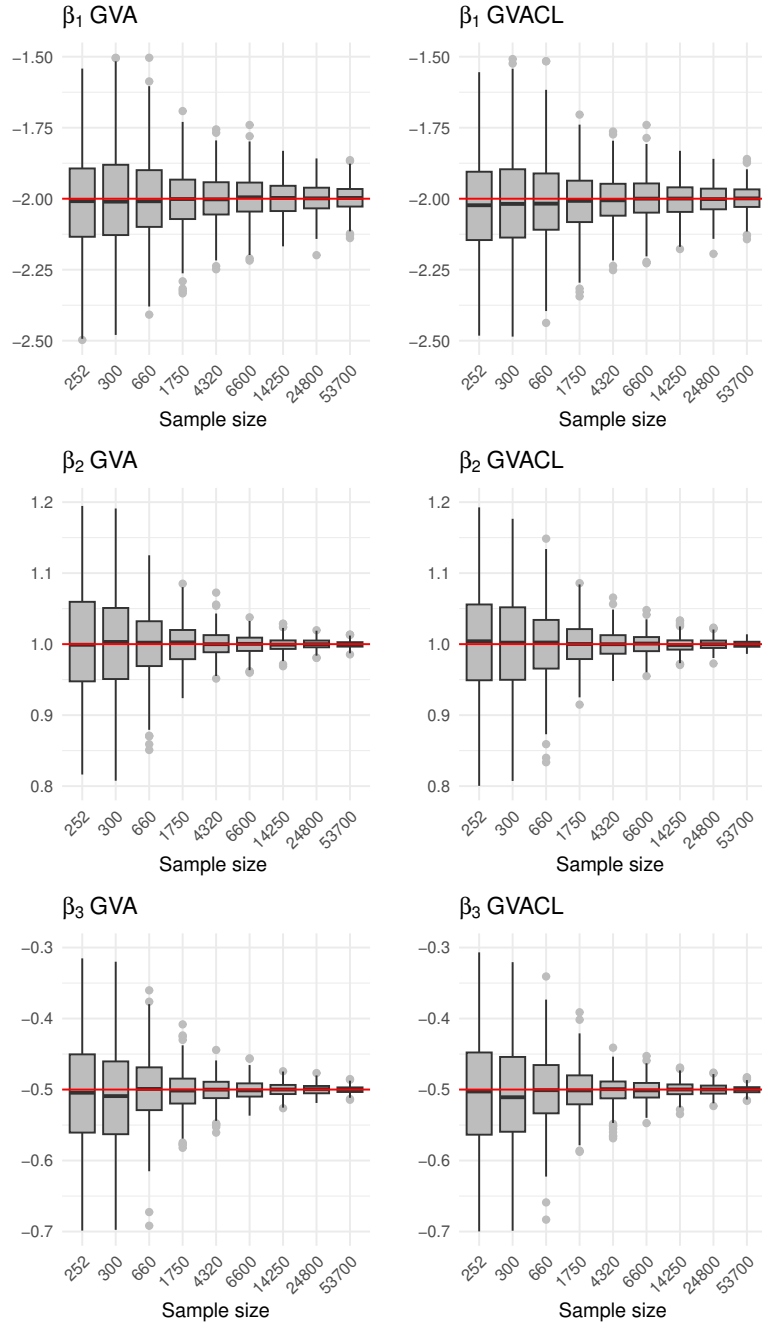


Figure S12: Boxplots of  $\beta_1, \beta_2$ , and  $\beta_3$  estimates obtained by GVA and GVACL for the Gamma regression model with crossed random effects based on 500 datasets. Red horizontal reference lines represent the true parameter values. The ratio  $\log m / \log n$  converges to 1.1.

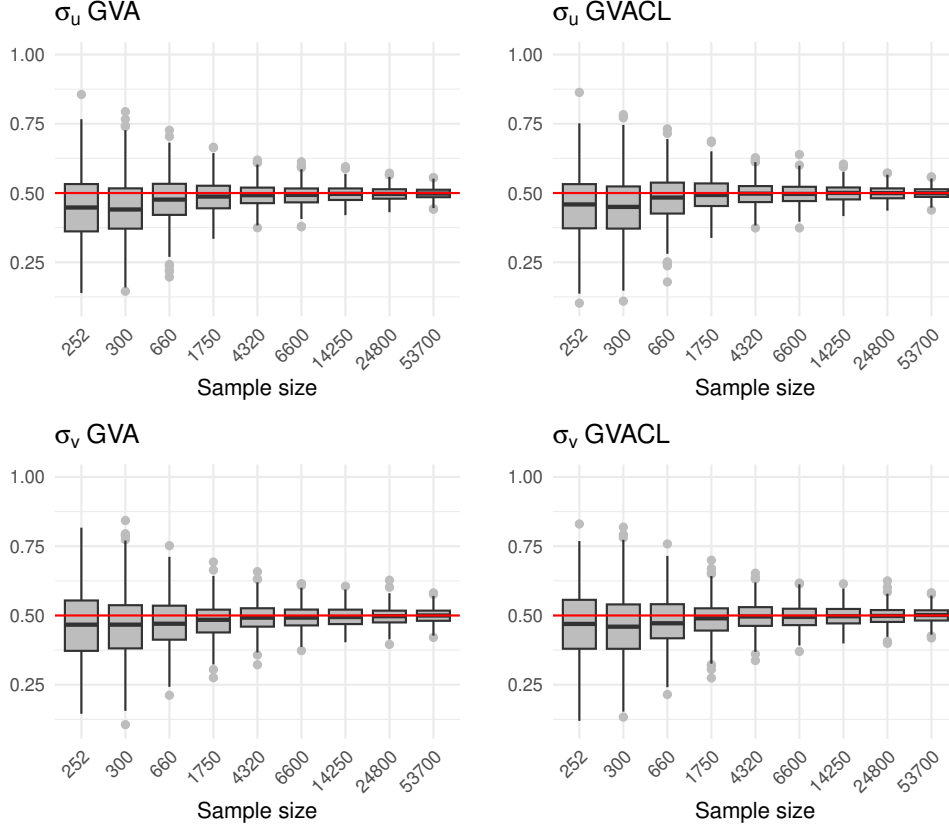


Figure S13: Boxplots of  $\sigma_u$  and  $\sigma_v$  estimates obtained by GVA and GVACL for the Gamma regression model with crossed random effects based on 500 datasets. Red horizontal reference lines represent the true parameter values. The ratio  $\log m / \log n$  converges to 1.1 .

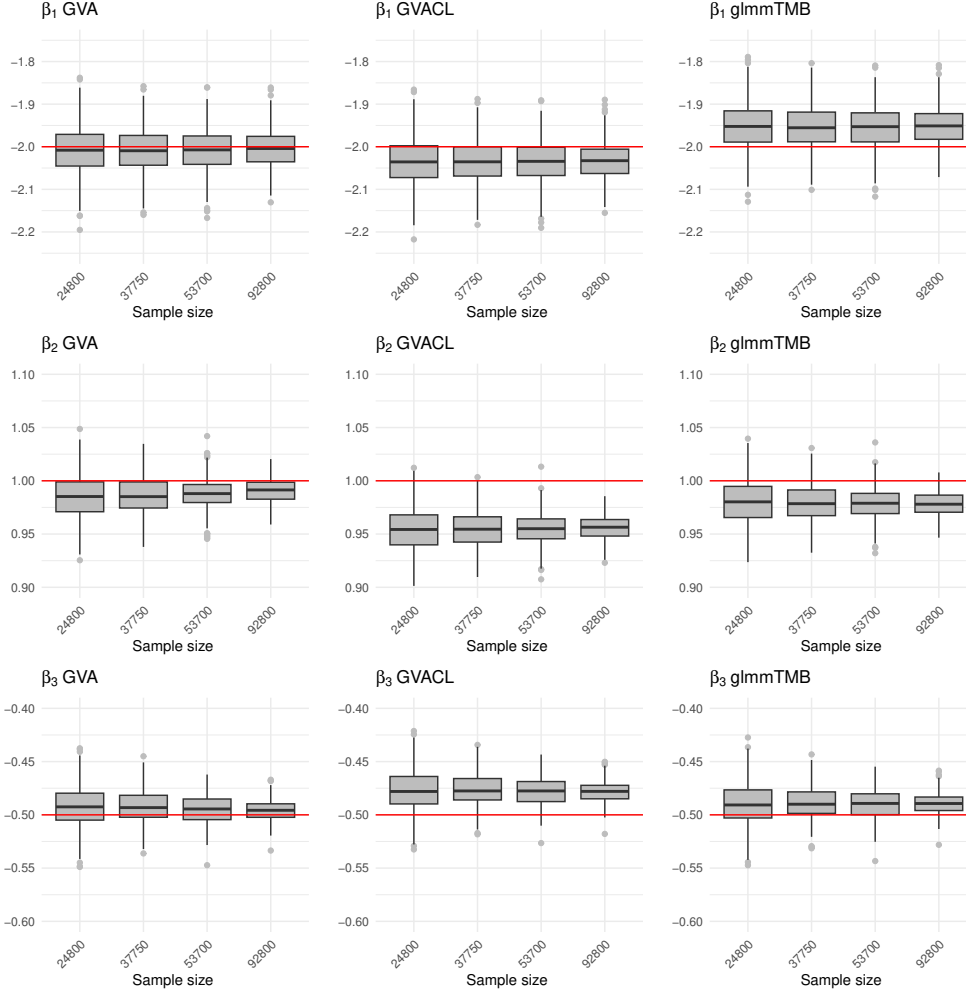


Figure S14: Boxplots of  $\beta_1, \beta_2$ , and  $\beta_3$  estimates obtained by GVA and GVACL for the logistic regression model with crossed random effects based on 500 datasets. Red horizontal reference lines represent the true parameter values. The ratio  $\log m / \log n$  converges to 1.1.

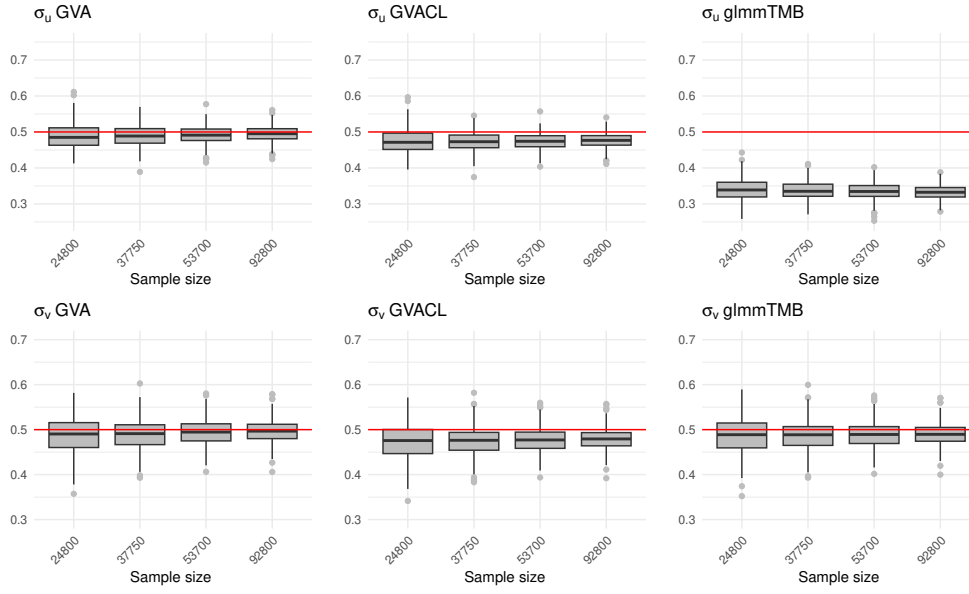


Figure S15: Boxplots of  $\sigma_u$  and  $\sigma_v$  estimates obtained by GVA and GVACL for the Gamma regression model with crossed random effects based on 500 datasets. Red horizontal reference lines represent the true parameter values. The ratio  $\log m / \log n$  converges to 1.1 .

## S7 Summary of the motor vehicle insurance data

In Table S1, we report the counts of claim events for each area and month,

Table S1: The counts of claim events for each area and month

| Area code | Jan. | Feb. | Mar. | Apr. | May  | Jun. | Jul. | Aug. | Sep. | Oct. | Nov. | Dec. |
|-----------|------|------|------|------|------|------|------|------|------|------|------|------|
| 01        | 5540 | 3388 | 4479 | 6840 | 7421 | 8068 | 5028 | 8841 | 6791 | 4982 | 1513 | 59   |
| 02        | 1100 | 610  | 811  | 1214 | 1338 | 1506 | 887  | 1443 | 1183 | 890  | 358  | 53   |
| 03        | 119  | 105  | 131  | 132  | 126  | 159  | 112  | 160  | 143  | 105  | 46   | 4    |
| 04        | 230  | 154  | 196  | 266  | 288  | 276  | 211  | 291  | 246  | 154  | 66   | 5    |
| 05        | 1240 | 734  | 1240 | 1580 | 1648 | 1853 | 1261 | 1853 | 1423 | 923  | 229  | 8    |
| 06        | 91   | 55   | 51   | 81   | 97   | 90   | 80   | 116  | 89   | 73   | 22   | 2    |
| 07        | 371  | 216  | 290  | 523  | 472  | 561  | 372  | 539  | 413  | 268  | 48   | 2    |
| 08        | 22   | 22   | 12   | 25   | 28   | 42   | 48   | 35   | 27   | 40   | 28   | 6    |
| 13        | 14   | 12   | 20   | 16   | 19   | 18   | 13   | 19   | 22   | 14   | 12   | 1    |
| 14        | 74   | 64   | 75   | 119  | 131  | 108  | 83   | 123  | 80   | 22   | 7    | 1    |
| 19        | 102  | 117  | 147  | 145  | 156  | 147  | 127  | 150  | 116  | 73   | 32   | 2    |
| 20        | 487  | 316  | 378  | 566  | 533  | 567  | 398  | 629  | 519  | 357  | 145  | 2    |
| 25        | 1347 | 818  | 976  | 1414 | 1590 | 1714 | 1170 | 1762 | 1306 | 963  | 233  | 20   |
| 26        | 251  | 143  | 203  | 352  | 364  | 420  | 243  | 470  | 316  | 193  | 50   | 1    |
| 27        | 515  | 311  | 454  | 711  | 827  | 902  | 594  | 973  | 701  | 323  | 106  | 2    |
| 31        | 179  | 115  | 151  | 212  | 227  | 299  | 179  | 347  | 245  | 122  | 56   | 1    |
| 33        | 519  | 327  | 436  | 557  | 605  | 676  | 412  | 723  | 583  | 410  | 122  | 9    |
| 34        | 453  | 210  | 381  | 589  | 679  | 706  | 449  | 835  | 645  | 446  | 120  | 14   |

We randomly selected one claim event from each area and month. A portion of the dataset can be found in Table S2.

Table S2:  $18 \times 12$  samples are randomly selected from 18 areas and 12 months. The deductible and the amount of claim are both in units of 10 million rupiahs.

| Month of occurence | Area code | Deductible | Amount of claim |
|--------------------|-----------|------------|-----------------|
| 1                  | 1         | 0.13       | 0.36            |
| 1                  | 2         | 0.02       | 0.21            |
| 1                  | 3         | 0.12       | 0.33            |
| 1                  | 4         | 0.02       | 0.10            |
| 1                  | 5         | 0.02       | 0.13            |
| 1                  | 6         | 0.02       | 0.39            |
| 1                  | 7         | 0.04       | 0.38            |
| 1                  | 8         | 0.16       | 0.35            |
| 1                  | 13        | 0.02       | 0.17            |
| 1                  | 14        | 0.02       | 0.02            |
| 1                  | 19        | 0.02       | 1.27            |
| 1                  | 20        | 0.02       | 0.05            |
| 1                  | 25        | 0.04       | 0.08            |
| 1                  | 26        | 0.02       | 0.06            |
| 1                  | 27        | 0.04       | 0.11            |
| 1                  | 31        | 0.02       | 1.53            |
| 1                  | 33        | 0.08       | 0.88            |
| 1                  | 34        | 0.06       | 0.08            |
| 2                  | 1         | 0.02       | 1.32            |
| 2                  | 2         | 0.02       | 1.29            |

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