## Web-based Supplementary Materials for "Additive Mixed Effect Model for Clustered Failure Time Data" by Jianwen Cai and Donglin Zeng

## Web Appendix

<u>Technical conditions for Theorems 1 and 2</u> To establish the asymptotic distributions of  $(\widehat{\boldsymbol{\beta}}, \widehat{\boldsymbol{\theta}})$  and  $\widehat{\Lambda}$ , we need the following conditions, where any subscript 0 means the true values.

- (C.1) For any constant  $\boldsymbol{\alpha}$  and a deterministic function  $\mu(t)$  satisfying  $\boldsymbol{\alpha} \neq 0$  or  $\mu(t) \neq 0$ ,  $P(\boldsymbol{\alpha}^T \mathbf{X}_{ij}(t) + \mu(t) = 0, j = 1, ..., n_i) < 1$ .
- (C.2) The true parameter  $H_0(t) = \Lambda_0(t) + G(t; \theta_0)$  is a right-continuous increasing function and satisfies  $H_0(\tau) < \infty$  and  $P(C_{ij} \ge \tau, \text{ for some } j = 1, ..., n_i) > 0$ .
- (C.3) The true parameter  $\theta_0$  belongs to a known bounded set  $\Theta$ . Moreover,

$$E\left\{\sum_{j\neq l,j,l=1}^{n_i} \int_0^{\tau} \int_0^{\tau} Y_{ij}(t) Y_{il}(s) \nabla_{\theta} Q(t,s;\theta) dt ds\right\}$$

is non-singular in a neighborhood of  $\theta_0$ , where  $\nabla_{\theta}Q(t,s;\theta)$  denotes the derivative of  $Q(t,s;\theta)$  with respect to  $\theta$ .

(C.4) The cluster size,  $n_i$ , is bounded and independent of  $Y_{ij}$ ,  $\mathbf{X}_{ij}$  and  $\Delta_{ij}$ . Additionally, the censoring time is assumed to be independent of  $T_{ij}$  and  $\xi_i$  given  $\mathbf{X}_{ij}$ .

Conditions (C.1) and (C.2) imply that the matrix

 $n^{-1}\sum_{i=1}^{n}\sum_{j=1}^{n_{i}}\int_{0}^{\tau}Y_{ij}(t)\{\mathbf{X}_{ij}(t)-\overline{\mathbf{X}}(t)\}^{\otimes 2}dt$  is positive definite when n is large enough. Thus,  $\widehat{\boldsymbol{\beta}}$  is well defined. This also implies that  $\boldsymbol{\Sigma}$  is invertible. Otherwise, suppose  $\boldsymbol{\alpha}^{T}\boldsymbol{\Sigma}\boldsymbol{\alpha}=0$  for some constant vector  $\boldsymbol{\alpha}$ . Then with probability one,  $\boldsymbol{\alpha}^{T}\{\mathbf{X}_{ij}(t)-\mu(t)\}=0$  for any t and  $j=1,...,n_{k}$ . However, from condition (C.3) this implies  $\boldsymbol{\alpha}=0$ . Thus,  $\boldsymbol{\Sigma}$  is positive definite. Additionally, condition (C.2) gives

 $n^{-1}\sum_{i=1}^{n}\sum_{j=1}^{n_i}Y_{ij}(t)$  is bounded away from zero. On the other hand, condition (C.3) ensures that the estimating equation for  $\theta$  has a solution which is a consistent estimator for  $\theta_0$ .

## Asymptotic expansion of $\widehat{\theta}$

To obtain the asymptotic distribution for  $\widehat{\theta}$ , we perform the first-order Taylor expansion at  $\theta = \theta_0$  on the left-hand side of (7). It yields

$$\mathbf{P}_{n} \left[ \sum_{j \neq l, j, l=1}^{n_{i}} \int_{0}^{\tau} \int_{0}^{\tau} Y_{ij}(t) Y_{il}(s) \left\{ d\widehat{\epsilon}_{ij}(t) d\widehat{\epsilon}_{il}(s) - Q(t, s; \theta_{0}) dt ds \right\} \right]$$

$$- \left[ E \left\{ \int_{0}^{\tau} \int_{0}^{\tau} Y_{ij}(t) Y_{il}(s) \nabla_{\theta} Q(t, s; \theta_{0}) dt ds \right\} + o_{p}(1) \right] (\widehat{\theta} - \theta_{0}) = 0.$$

Note

$$\begin{aligned} &\mathbf{P}_{n}\left[\sum_{j\neq l,j,l=1}^{n_{i}}\int_{0}^{\tau}\int_{0}^{\tau}Y_{ij}(t)Y_{il}(s)\left\{d\widehat{\epsilon}_{ij}(t)d\widehat{\epsilon}_{il}(s)-Q(t,s;\theta_{0})dtds\right\}\right]\\ &=\left(\mathbf{P}_{n}-\mathbf{P}\right)\left[\sum_{j\neq l,j,l=1}^{n_{i}}\int_{0}^{\tau}\int_{0}^{\tau}Y_{ij}(t)Y_{il}(s)\left\{d\epsilon_{ij0}(t)d\epsilon_{il0}(s)-Q(t,s;\theta_{0})dtds\right\}\right]\\ &-E\left[\sum_{j\neq l,j,l=1}^{n_{i}}\int_{0}^{\tau}\int_{0}^{\tau}Y_{ij}(t)Y_{il}(s)\left\{d\widehat{H}(t)-dH_{0}(t)+\mathbf{X}_{ij}(t)^{T}(\widehat{\boldsymbol{\beta}}-\boldsymbol{\beta}_{0})dt\right\}d\epsilon_{il0}(s)\right]\\ &-E\left[\sum_{j\neq l,j,l=1}^{n_{i}}\int_{0}^{\tau}\int_{0}^{\tau}Y_{ij}(t)Y_{il}(s)d\epsilon_{ij0}(t)\left\{d\widehat{H}(s)-dH_{0}(s)+\mathbf{X}_{il}(t)^{T}(\widehat{\boldsymbol{\beta}}-\boldsymbol{\beta}_{0})ds\right\}\right].\end{aligned}$$

Thus, from equations (A.1) and (A.2), we obtain

$$\widehat{\theta} - \theta_0 = (\mathbf{P}_n - \mathbf{P})S_{\theta}(\mathbf{O}_i) + o_n(n^{-1/2})$$

where

$$S_{\theta}(\mathbf{O}_{i}) = \left[ E \left\{ \sum_{j \neq l, j, l=1}^{n_{i}} \int_{0}^{\tau} \int_{0}^{\tau} Y_{ij}(t) Y_{il}(s) \nabla_{\theta} Q(t, s; \theta_{0}) dt ds \right\} \right]^{-1}$$

$$\times \left\{ \sum_{j \neq l, j, l=1}^{n_{i}} \int_{0}^{\tau} \int_{0}^{\tau} Y_{ij}(t) Y_{il}(s) \left\{ d\epsilon_{ij0}(t) d\epsilon_{il0}(s) - Q(t, s; \theta_{0}) dt ds \right\} \right.$$

$$- E \left[ \sum_{j \neq l, j, l=1}^{n_{i}} \int_{0}^{\tau} \int_{0}^{\tau} Y_{ij}(t) Y_{il}(s) \left\{ dS_{H}(\mathbf{O}_{i}; t) + \mathbf{X}_{ij}(t)^{T} S_{\boldsymbol{\beta}}(\mathbf{O}_{i}) dt \right\} d\epsilon_{il0}(s) \right]$$

$$- E \left[ \sum_{i \neq l, j, l=1}^{n_{i}} \int_{0}^{\tau} \int_{0}^{\tau} Y_{ij}(t) Y_{il}(s) d\epsilon_{ij0}(t) \left\{ dS_{H}(\mathbf{O}_{i}; s) + \mathbf{X}_{il}(t)^{T} S_{\boldsymbol{\beta}}(\mathbf{O}_{i}) ds \right\} \right] \right\}.$$

Consistent estimation of asymptotic variance. Clearly, the asymptotic covariance of  $(\widehat{\boldsymbol{\beta}}, \widehat{H}, \widehat{\boldsymbol{\theta}})$  is given by the covariance of the corresponding influence function  $(\mathbf{S}_{\boldsymbol{\beta}}, S_H, S_{\boldsymbol{\theta}})$ . Thus, a consistent estimator of the asymptotic covariance can be obtained from the empirical covariance of  $(\widehat{\mathbf{S}}_{\boldsymbol{\beta}}, \widehat{S}_H, \widehat{S}_{\boldsymbol{\theta}})$ , where the latter are the consistent estimators of  $(\mathbf{S}_{\boldsymbol{\beta}}, S_H, S_{\boldsymbol{\theta}})$ . Particularly, we can choose

$$\widehat{S}_{\boldsymbol{\beta}}(\mathbf{O}_{i}) = \left[ n^{-1} \sum_{i=1}^{n} \sum_{j=1}^{n_{i}} \int_{0}^{\tau} Y_{ij}(t) \{ \mathbf{X}_{ij}(t) - \overline{\mathbf{X}}(t) \}^{\otimes 2} dt \right]^{-1} \sum_{j=1}^{n_{i}} \int_{0}^{\tau} Y_{ij}(t) \{ \mathbf{X}_{ij}(t) - \overline{\mathbf{X}}(t) \} d\widehat{\epsilon}_{ij}(t),$$

$$\widehat{S}_{H}(\mathbf{O}_{i}; s) = \int_{0}^{s} \frac{\sum_{j=1}^{n_{i}} Y_{ij}(t) d\widehat{\epsilon}_{ij}(t)}{n^{-1} \sum_{i=1}^{n} \sum_{j=1}^{n_{i}} Y_{ij}(t)} - \int_{0}^{s} \overline{\mathbf{X}}(t)^{T} dt \widehat{S}_{\boldsymbol{\beta}}(\mathbf{O}_{i}),$$

and

$$\widehat{S}_{\theta}(\mathbf{O}_{i}) = \left\{ n^{-1} \sum_{i=1}^{n} \sum_{j \neq l, j, l=1}^{n_{i}} \int_{0}^{\tau} \int_{0}^{\tau} Y_{ij}(t) Y_{il}(s) \nabla_{\theta} Q(t, s; \widehat{\theta}) dt ds \right\}^{-1} \\
\times \left\{ \sum_{j \neq l, j, l=1}^{n_{i}} \int_{0}^{\tau} \int_{0}^{\tau} Y_{ij}(t) Y_{il}(s) \left\{ d\widehat{\epsilon}_{ij}(t) d\widehat{\epsilon}_{il}(s) - Q(t, s; \widehat{\theta}) dt ds \right\} \right. \\
\left. - n^{-1} \sum_{k=1}^{n} \left[ \sum_{j \neq l, j, l=1}^{n_{k}} \int_{0}^{\tau} \int_{0}^{\tau} Y_{kj}(t) Y_{kl}(s) \left\{ d\widehat{S}_{H}(\mathbf{O}_{i}; t) + \mathbf{X}_{kj}(t)^{T} \widehat{S}_{\boldsymbol{\beta}}(\mathbf{O}_{i}) dt \right\} d\widehat{\epsilon}_{kl}(s) \right] \\
\left. - n^{-1} \sum_{k=1}^{n} \left[ \sum_{j \neq l, j, l=1}^{n_{k}} \int_{0}^{\tau} \int_{0}^{\tau} Y_{kj}(t) Y_{kl}(s) d\widehat{\epsilon}_{kj}(t) \left\{ d\widehat{S}_{H}(\mathbf{O}_{i}; s) + \mathbf{X}_{kl}(t)^{T} \widehat{S}_{\boldsymbol{\beta}}(\mathbf{O}_{i}) ds \right\} \right] \right\}.$$