1. induced smoothing method to Quantile residual life model fitting estimating equation (Kim et al.(2012))
Estimaitng Equation

$$S(\beta) = \sum_{i=1}^{n} w_i I[Z_i > t_0] X_i \psi_\tau \{ \log(Z_i - t_0) - X_i^T \beta \} = 0$$

Using induced smoothing

$$\begin{split} \bar{S}(\beta) &= E_z[S(\beta + \Gamma^{\frac{1}{2}}D)] \\ &= E_Z[\sum_{i=1}^n w_i I[Z_i > t_0] X_i \psi_\tau \{\log(Z_i - t_0) - X_i^T(\beta + \Gamma^{\frac{1}{2}}D)\}] \\ &= E_Z[\sum_{i=1}^n w_i I[Z_i > t_0] X_i (\tau - I\{\log(Z_i - t_0) - X_i^T(\beta + \Gamma^{\frac{1}{2}}D) \le 0\})] \\ &= \sum_{i=1}^n w_i I[Z_i > t_0] X_i (\tau - E_z[I\{\log(Z_i - t_0) - X_i^T(\beta + \Gamma^{\frac{1}{2}}D) \le 0\}]) \\ &= \sum_{i=1}^n w_i I[Z_i > t_0] X_i (\tau - P[X_i^T \Gamma^{\frac{1}{2}}D \ge \log(Z_i - t_0) - X_i^T \beta]) \\ &= \sum_{i=1}^n w_i I[Z_i > t_0] X_i (\tau - P[D \ge \frac{\log(Z_i - t_0) - X_i^T \beta}{\sqrt{X_i^T \Gamma X_i}}]) \\ &= \sum_{i=1}^n w_i I[Z_i > t_0] X_i (\tau - 1 + \Phi(\frac{\log(Z_i - t_0) - X_i^T \beta}{\sqrt{X_i^T \Gamma X_i}})) \end{split}$$

where $D \sim N_P(0, I_P)$, $Z_i = min(T_i, C_i)$ and X_i is covariate.

2. Sandwich estimator $A(\beta)$

$$A(\beta) = \frac{\partial U(\beta)}{\partial \beta}$$

$$= \frac{\partial \sum w_i I[Z_i > T_0] X_i \left(\tau - 1 + \Phi\left(\frac{\log(Z_i - t_0) - X_i^T \beta}{\sqrt{X_i^T \Gamma X_i}}\right)\right)}{\partial \beta}$$

$$= \sum w_i I[Z_i > T_0] X_i \phi\left(\frac{\log(Z_i - t_0) - X_i^T \beta}{\sqrt{X_i^T \Gamma X_i}}\right) \left(\frac{-X_i^T}{\sqrt{X_i^T \Gamma X_i}}\right)$$