Table S1. Hypothesis tests for two-sample survival data

No.	Name	Test statistic	Notations
1	Weighted Log-rank	$Z=\frac{[\sum_{j=1}^{\tau}W(t_j)(d_{1j}-n_{1j}\left(\frac{d_j}{n_j}\right))]^2}{\sum_{j=1}^{\tau}W(t_j)^2\left(\frac{n_{1j}}{n_j}\right)\left(1-\frac{n_{1j}}{n_j}\right)\left(\frac{n_j-d_j}{n_j-1}\right)d_j}\sim\chi^2(1)$	$W(t_j)=1$, Logrank test (LR); $W(t_j)=n_j$, Gehan-Wilcoxon test (GW); $W(t_j)=\sqrt{n_j}$, Tarone-Ware test (TW); $W(t_j)=[S(t_{j-1})]^{\rho}[1-S(t_{j-1})]^{\gamma}$ with $\rho\geq 0$, $\gamma\geq 0$. Fleming-Harrington test ($G^{\rho,\gamma}$), where d_{ij} is the number of events in the ith group (i=1, 2) out of n_{ij} individuals (at risk) at time t_j and $d_j=d_{1j}+d_{2j}$, $n_j=n_{1j}+n_{2j}$.
2	Renyi(RY)	$Q=\sup\{\lvert\tilde{Z}(t_j)\rvert, t_j\leq\tau\}/\sigma(\tau)$	$\tilde{Z}(t_j)=\sum_{t_k\leq t_j}W(t_k)\left[d_{1k}-n_{1k}\left(\frac{d_k}{n_k}\right)\right], j=1,2,...\tau,$ $\sigma^2(\tau)=\sum_{t_k\leq\tau}W(t_k)^2\left(\frac{n_{1k}}{n_k}\right)\left(\frac{n_{2k}}{n_k}\right)\left(\frac{n_k-d_k}{n_k-1}\right)d_k$
3	Modified Kolmogorov-Smirnov(MKS)	$y=\sup_{0\leq t\leq T}\lvert Y(t)\rvert$	$Y_{N_1,N_2}(t)=\frac{1}{2}\{\hat{S}_1(t)+\hat{S}_2(t)\}\int_0^t\{\frac{N_1\hat{C}_1(s-)N_2\hat{C}_2(s-)}{N_1\hat{C}_1(s-)+N_2\hat{C}_2(s-)}\}^{\frac{1}{2}}\times I_{\{N_1(s)N(s)>0\}}d\{\hat{H}_1(s)-\hat{H}_2(s)\}$ $T=\max\{t_j:N_1(t_j)N_2(t_j)>0\}$
4	Cramer-von Mises(CVM)	$\int_0^{\tau}[\int_0^{t}K(s)d\{\hat{A}(s)-\hat{A}_0^*(s)\}]^2dH(s)$	CVM1 statistic uses untransformed process, which is asymptotic to a standard Brownian motion process, another CVM2 statistic converges to a Brownian bridge process

5	Weighted Kaplan-Meier (WKM)	$V_{wkm}=\sqrt{\frac{N_1N_2}{N_1+N_2}}\int_0^{T_m}\widetilde{w}(t)[\widehat{S_2}(t)-\widehat{S_1}(t)]dt$ $\hat{\sigma}^2_{wkm}=-\int_0^{T_m}\left\{\int_t^{T_m}\left[\widetilde{w}(s)\hat{S}(s)\right]ds\right\}^2\frac{N_1\widehat{C_1}(t-)+N_2\widehat{C_2}(t-)}{(N_1+N_2)\widehat{C_1}(t-)\widehat{C_2}(t-)}\frac{d\hat{S}(t)}{\hat{S}(t)\hat{S}(t-)}$	$T_m=\sup\{t:\min\{\widehat{C_1}(t),\widehat{C_2}(t),\widehat{S_1}(t),\widehat{S_2}(t)\}>0\}$ $\widetilde{w}(t)=\frac{(N_1+N_2)\widehat{C_1}(t-)\widehat{C_2}(t-)}{N_1\widehat{C_1}(t-)+N_2\widehat{C_2}(t-)}$
6	Maximum Weighted Kaplan-Meier (MKM)	$\widetilde{V}=\max\lvert\widetilde{V}_\ell\rvert$	$V_l=\sqrt{\frac{N_1N_2}{N_1+N_2}}\int_0^{\tau}f\{\hat{S}(t-)\}\widetilde{w}(t)[\hat{S}_1(t)-\hat{S}_2(t)]dt$ $f\{S(t-)\}=[S(t-)]^{\rho}[1-S(t-)]^{\gamma},\rho=0,1,2;\gamma=0,1,2$ $\widetilde{V}_\ell=V_\ell/(\hat{\sigma}_{\ell,\ell})^{1/2},\ell=1,\ldots,m(m=9)$
7	Lee's versatile test(SHL)	$SHL1$: $\lvert Z_1+Z_2\rvert/2$ $SHL2$: $(\lvert Z_1\rvert+\lvert Z_2\rvert)/2$ $SHL3$: $\max(\lvert Z_1\rvert,\lvert Z_2\rvert)$	Z_1 and Z_2 are calculated as Z_1 with weight function ρ=0, γ=1; Z_2 with weight function ρ=1, γ=0;
8	Lin and Wang's test(LW)	$T^*=\frac{\Delta-E(\Delta)}{\sqrt{Var(\Delta)}}\sim N(0,1)$	$\Delta=\sum_{j=1}^{\tau}\left[d_{1j}-E(d_{1j})\right]^2$ $E(\Delta)=\sum_{j=1}^{\tau}\frac{n_{1j}n_{2j}d_j(n_j-d_j)}{n_j{}^2(n_j-1)}$ $Var(\Delta)=\sum_{j=1}^{\tau}\{E(d_{1j}^4)-4E(d_{1j}^3)E(d_{1j})+6E(d_{1j}^2)(E(d_{1j}))^2-3(E(d_{1j}))^4-(Var(d_{1j}))^2\}$

9	Lin and Xu's test (LX)	$\Delta^* = \frac{\Delta - \widehat{E}(\Delta)}{\sqrt{\widehat{Var}(\Delta)}} \sim N(0,1)$	$\Delta = \sum_{t_j<\tau} \lvert \widehat{S}_1(t_j) - \widehat{S}_2(t_j) \rvert (t_{j+1} - t_j)$ $\widehat{E}(\Delta) = \sum_{j \mid t_j<\tau} \{\frac{2}{\pi}[\widehat{\sigma}^2_{S_1}(t_j) + \widehat{\sigma}^2_{S_2}(t_j)]\}^{1/2}(t_{j+1} - t_j)$ $\widehat{Var}(\Delta) = \sum_{j \mid t_j<\tau} (t_{j+1} - t_j)^2(1-\frac{2}{\pi})[\widehat{\sigma}^2_{S_1}(t_j) + \widehat{\sigma}^2_{S_2}(t_j)] + \sum_{j<j' \mid t_j, t_{j'}<\tau} 2\rho_{j,j'}(t_{j+1} - t_j)(t_{j'+1} - t_{j'})(1-\frac{2}{\pi})$ $\times\{[\widehat{\sigma}^2_{S_1}(t_j) + \widehat{\sigma}^2_{S_2}(t_j)][\widehat{\sigma}^2_{S_1}(t_{j'}) + \widehat{\sigma}^2_{S_2}(t_{j'})]\}^{1/2}$
10	Two-stage(TS)	$V = \sup_{\tau_\varepsilon \le m \le \tau - \tau_\varepsilon} (V_m)$	$V_m = \sum_{j=1}^{\tau} w_j^{(m)}(d_{1j} - n_{1j}\frac{d_j}{n_j}) \Big/ \sqrt{\sum_{j=1}^{\tau} (w_j^{(m)})^2 \left(\frac{n_{1j}}{n_j}\right)\left(\frac{n_{2j}}{n_j}\right)\left(\frac{n_j - d_j}{n_j - 1}\right) d_j}$ $w_j^{(m)} = \begin{cases} -1, & j = 1,2...m \\ c_m, & j = m+1,...\tau \end{cases}$
11	Adaptive Neyman's Smooth tests (NY)	$T_d = U(\tau)^{\mathrm{T}} \widehat{\sigma}(\tau)^{-} U(\tau)$ $T_s = \max\{V_C(\tau)^{\mathrm{T}} \sigma_{CC}(\tau)^{-1} V_C(\tau) : C \in \zeta, \lvert C \rvert = d^*\}$	T_d : fixed-dimensional test(NY1) T_s : data-driven test(NY2) $V_C(\tau)$ and $\widehat{\sigma}_{CC}(\tau)$ are the subvector and submatrix of $V(\tau)$ and $\sigma(\tau)$ corresponding to the subset *C*. Schwarz's criterion is given as $S = \arg\max_{C \in \zeta}\{T_C - \lvert C \rvert \log n\}$.