

# Supplementary Materials

In the following sections we present detailed information about the derivations for the tree-ensemble models, perform a simulation study comparing the proposed models with other survival models, and discuss convergence and computational time for our proposed models. In addition, we present additional findings for the application of the tree-ensemble models to the breast cancer and brain tumor data sets.

## 1 Model derivation

We denote the observed data for the  $i$ th patient ( $i = 1, \dots, n$ ) as  $t_i$ , the survival time, along with  $\delta_i$ , the event indicator function, where  $\delta_i = 0$  if the data are right censored and  $\delta_i = 1$  if they are not. In addition to the survival response, the  $p$ -dimensional vector of the covariates (genes/probes) potentially associated with the  $i$ th patient survival time,  $\mathbf{X}_i$ , is also available. Let  $\mathbf{t} = (t_1, \dots, t_n)$  denote the vector of the survival times and let  $\mathbf{X}_{n \times p}$  denote the matrix of the gene expression data. In the following sections, we develop the survival distribution, which aids to predict the survival time of a new patient with covariates  $X_{\text{new}}$ .

Modeling the survival data usually proceeds in two steps: (1) specification of a sampling distribution  $p(\mathbf{t}|f(\mathbf{X}))$ , conditional on a function of the covariates  $f(\mathbf{X})$ , such as modeling either the hazard function (as in CPH models) or directly modeling the survival time (as in Weibull and AFT models) and (2) specification of the regression function  $f(\mathbf{X})$ , which models the covariate effects. For computational convenience, the covariates are usually assumed to be linear and independently related to survival, such that  $f(\mathbf{X}) = \mathbf{X}'\beta$  where  $\beta$  is a vector of  $p$  unknown regression coefficients that captures the covariate effects on the survival time or hazard. There are two drawbacks to this approach. First, the linear and independent assumption is a restrictive one. Second, and more importantly, in high-throughput studies such as those based on gene expression data, the problem becomes much more complex when  $p$ , the dimension of  $\mathbf{X}$ , is very large, possibly larger than the sample size  $n$ . This makes the estimation of  $\beta$  unstable and exacerbates the high-dimensionality problem if interactions between covariates are considered. Dimension reduction approaches such as feature selection or partial least squares methods alleviate this problem to a certain degree. However, these methods are based on a linear relationship between the response and the covariate, which may not be very realistic. If the actual  $f$  is nonlinear, these models may fail to produce a reasonable prediction due to a lack of flexibility. We propose to model  $f(\mathbf{X})$  in a flexible manner using ensemble

methods that not only accommodate nonlinear effects but which also incorporate the interactions of the covariates to estimate the effects on survival time.

## 1.1 CPH model

Let the joint conditional survival function of  $\mathbf{t}$  in the CPH model can be written as

$$S((t)|\omega, \Lambda) = \exp\left(-\sum \Lambda(t_i)\exp(\omega_i)\right)$$

where  $\Lambda$  represents the cumulative hazard function. We then specify a Gamma process prior for  $\Lambda$ , such that  $\Lambda \sim \mathcal{GP}(a\Lambda^*, a)$  where  $\Lambda^*$  is the mean process and  $a$  is a weight parameter about the mean with  $\Lambda(t) \sim \text{Gamma}(a\Lambda^*(t), a)$ . The  $\Lambda$  vector can be integrated out such that the marginal likelihood of  $\omega$  with some right censoring can be written as

$$L(t|\omega) = \exp\left(-\sum aW_i\Lambda^*(t_i)\right) \prod \left(a\lambda^*(t_i)W_i\right)^{\delta_i}$$

where  $\delta_i$  is the indicator for event,  $V_i = \sum_{l \in R(t_i)} \exp(\omega_l)$ ,  $i = 1, \dots, n$ ,  $R(t_i)$  is the set of individuals at risk at time  $t_i$ , and  $W_i = -\log\{1 - \exp(\omega_i)/(a + V_i)\}$ .

The full conditional is written as

$$\begin{aligned} p(\omega|\Lambda, \mathbf{X}, \sigma^2, t, \delta) &\propto \exp\left(-\sum_{i=1}^n aW_i\Lambda^*(t_i)\right) \prod_{i=1}^n \left(a\lambda^*(t_i)W_i\right)^{\delta_i} \\ &\times \exp\left(-\frac{1}{2\sigma^2}(\omega - f(\mathbf{X}))' \mathbf{I}(\omega - f(\mathbf{X}))\right) \\ &\propto -\sum aW_i\Lambda^*(t_i) + d \sum \log(a\lambda^*(t_i)W_i) + \text{MVN}(f(\mathbf{X}), \sigma^2 \mathbf{I}) \end{aligned}$$

and the a M-H procedure is used to simulate the posterior distribution of  $\omega$ . The joint posterior survival function can be written as

$$S(t|\omega) = \left(\frac{a}{a + \exp(\omega)}\right)^{a\Lambda^*}$$

## 1.2 Weibull model

The joint likelihood function for  $\omega$  and  $\tau$  in the Weibull model is given by

$$\begin{aligned}
L(\tau, \omega | \mathbf{X}, t, \delta) &= \prod_{i=1}^n f(t_i | \tau, \omega_i)^{\delta_i} S(t_i | \tau, \omega_i)^{1-\delta_i} \\
&= \tau^{\sum \delta_i} t_i^{\sum \delta_i (\tau-1)} \exp\left(\sum_{i=1}^n \delta_i \omega_i - \sum_{i=1}^n \delta_i \exp(\omega_i) t_i^\tau - \sum_{i=1}^n (1-\delta_i) \exp(\omega_i) t_i^\tau\right) \\
&= \tau^\Delta t_i^{\sum \delta_i (\tau-1)} \exp\left(\sum_{i=1}^n \delta_i \omega_i - \sum_{i=1}^n \exp(\omega_i) t_i^\tau\right) \\
&= \tau^\Delta \exp\left(\sum_{i=1}^n \delta_i \omega_i + \sum_{i=1}^n \delta_i (\tau-1) \log(t_i) - \sum_{i=1}^n \exp(\omega_i) t_i^\tau\right) \\
&= \tau^\Delta \exp\left(\sum_{i=1}^n (\delta_i \omega_i + \delta_i (\tau-1) \log(t_i)) - \sum_{i=1}^n \exp(\omega_i) t_i^\tau\right)
\end{aligned}$$

where  $\Delta = \sum \delta_i$ . For convenience, we let  $\theta = \log(\tau)$  and write the conditional distribution of the vector of  $\omega$ 's as

$$\begin{aligned}
p(\omega | \mathbf{X}, t, \delta, \theta) &\propto \exp\left(\theta \Delta + \sum_{i=1}^n (\delta_i \omega_i + \delta_i (e^\theta - 1) \log(t_i)) - \sum_{i=1}^n \exp(\omega_i) t_i^{e^\theta}\right) \\
&\quad \times \exp\left(-\frac{1}{2\sigma^2} (\omega - f(\mathbf{X}))' \mathbf{I} (\omega - f(\mathbf{X}))\right)
\end{aligned}$$

Since  $\omega_i$ 's are conditionally independent, we conveniently draw their posterior distributions componentwise from

$$\begin{aligned}
p(\omega_i | \omega_{l \neq i}, \mathbf{X}, t, \delta, \theta) &\propto \exp\left(\theta \Delta + \delta_i \omega_i + \delta_i (e^\theta - 1) \log(t_i) - \exp(\omega_i) t_i^{e^\theta}\right) \\
&\quad \times \exp\left(-\frac{1}{2\sigma^2} (\omega_i - f(\mathbf{X}_i))^2\right)
\end{aligned}$$

Following, we also use M-H to draw the conditional of  $\theta$  from

$$\begin{aligned}
p(\theta | \omega, \mathbf{X}, t, \delta) &\propto \exp\left(\theta \Delta + \sum_{i=1}^n (\delta_i \omega_i + \delta_i (e^\theta - 1) \log(t_i)) - \sum_{i=1}^n \exp(\omega_i) t_i^{e^\theta}\right) \\
&\quad \times e^{\theta(\tau_o-1)} e^{-k_o e^\theta} e^\theta
\end{aligned}$$

## 1.3 AFT model

We use a data augmentation approach to impute censored values in the AFT model. Let  $\omega$  be a latent variable such that  $\omega_i = f(\mathbf{X}_i) + \epsilon_i$ , where  $\epsilon_i$ 's are i.i.d.  $Normal(0, \sigma^2)$ . The model can now be expressed as

$$\begin{cases} \log(t_i^*) = \alpha + \omega_i & \text{if } \delta_i = 1 \\ \log(t_i^*) > \alpha + \omega_i & \text{if } \delta_i = 0 \end{cases}$$

After estimating  $\omega$ , we define  $r_i = \log(t_i^*) - \omega_i$  where  $[r | \alpha, \sigma^2] \sim Normal(\alpha, \sigma^2)$ . Now, we specify a conjugate prior for  $\alpha$  as  $[\alpha] \sim Normal(\alpha_o, c)$ , which makes the posterior distribution of  $\alpha$  be an

updated normal

$$[\alpha|r, \sigma^2, \alpha_o, c] \sim Normal(\alpha^*, \sigma^*)$$

where  $\alpha^* = \frac{\sigma^2 \alpha_o + c(\sum |r_i|)}{\sigma^2 + nc}$  and  $\sigma^* = \sqrt{\frac{c\sigma^2}{\sigma^2 + nc}}$ . Thus, the censored survival times ( $\delta_i = 0$ ) are sampled from univariate normal distributions  $Normal(\alpha + \omega_i, \sigma^2)$  truncated at  $\log(t_i)$ .

## 2 Performance Assessment

### 2.1 Breast Cancer Data

We compared the performance of our method with other survival prediction methods tailored for gene expression data as recently reviewed by van Wieringen *et al.*, (2009) and other popular survival methods. We used the breast cancer data set of Van't Veer *et al.*, (2002;

<http://www.rii.com/publications/2002/vantveer.html>), which contains gene expression profiles for 295 breast cancer patients and 5,057 gene expression values, along with patient survival outcomes. Around 73% of these observations are right censored. Patient age ranges from 26 to 53 years and the percentage of patients with tumor grade I is 34%, grade II is 40%, and grade III is 26%. We reapplied the “best” methods found by van Wieringen *et al.*, (2009): multivariable linear CPH model (CPH), L1-penalized Cox regression (CPH-L1) of Tibshirani (1997), and the L2-penalized Cox regression (CPH-L2) of Gui & Li (2005). We replicate the same setup used by van Wieringen *et al.* (2009) to allow comparisons across studies, i.e., we use the multivariable linear CPH model, in which the top 10 genes were obtained using a univariable Cox regression. In addition, we ran a multivariable linear Weibull model, in which the top 10 most significant genes were obtained by univariable Weibull models. We also used a multivariable linear AFT model, in which the top 10 genes were pre-selected by using a univariable AFT analysis. We also included conditional inference tree ensemble methods as Bagging, Random Forest (Hothorn *et al.*, 2006), and Survival Random Forests (ntree = 2000; Ishwaran *et al.*, 2008) as well as CoxBoost (Binder & Schumacher, 2009). Bagging and Random Forest models were also studied by van Wieringen *et al.*, (2009). Similarly to van Wieringen *et al.* (2009), we used the top 200 most significant genes obtained by the underlying univariable model to run our ensemble versions of the accelerated failure time model (AFT-TREE), the Weibull model (WEI-TREE), and the CPH model (CPH-TREE). We used a long single chain of  $K = 10,000$  iterations for each survival model with a burn-in of the first 5,000 samples. In addition, we ran several chains with different initial values and found that our results are robust to these

convergence checks. We repeated the cross-validation procedure 50 times with the data randomly split into training and test sets in a 2:1 ratio and with the number of censored observations kept balanced between training and test sets. We used the training set to build the predictor and then used the test set to assess the performance of the competing methods. Table 1 summarizes our results.

Table 1: Quartiles of the performance measures applied to the test sets of 50 random splits of the breast cancer data. **BS** stands for Brier score,  $R^2$  for coefficient of determination, and **CI** for Concordance Index. The top 3 best methods in each performance measure are identified by an asterisk.

Method	BS(50%)	BS(25%,75%)	$R^2$ (50%)	$R^2$ (25%,75%)	CI(50%)	CI(25%,75%)
AFT	0.180	[0.121,0.226]	0.140	[0.042,0.212]	0.603*	[0.558,0.638]
WEI	0.163	[0.120,0.212]	0.145	[0.095,0.220]	0.583	[0.545,0.638]
CPH	0.169	[0.109,0.216]	0.152	[0.108,0.193]	0.586	[0.555,0.637]
CPH-L1	0.181	[0.121,0.238]	0.174*	[0.088,0.224]	0.582	[0.543,0.646]
CPH-L2	0.175	[0.116,0.211]	0.155	[0.092,0.206]	0.592	[0.552,0.644]
Bagging	0.165	[0.118,0.221]	0.155*	[0.083,0.236]	0.591	[0.541,0.626]
RF	0.188	[0.148,0.223]	0.156*	[0.084,0.223]	0.583	[0.542,0.627]
RSF	0.193	[0.135,0.226]	0.146	[0.081,0.229]	0.571	[0.535,0.615]
CoxBoost	0.162*	[0.107,0.198]	0.145	[0.056,0.211]	0.600*	[0.554,0.634]
AFT-TREE	0.158*	[0.106,0.205]	0.141	[0.084,0.213]	0.593	[0.548,0.633]
WEI-TREE	0.160*	[0.105,0.216]	0.136	[0.081,0.211]	0.582	[0.541,0.607]
CPH-TREE	0.164	[0.111,0.210]	0.119	[0.060,0.199]	0.598*	[0.557,0.647]

As stated previously, one of the advantages of ensemble methods is that they allow us to assess the importance of each covariate for survival prediction using the relative frequency of occurrence. Using an Bayesian FDR cutoff of 0.1, we found that a total of 9 variables were significant in the CPH-TREE, 7 in the WEI-TREE, and 11 in the AFT-TREE (Table 2). One gene (BCL2) was simultaneously listed for the AFT-TREE and the WEI-TREE. Genes identified by the models could represent promising targets for further biological investigation. A search of the OMIM database (<http://www.ncbi.nlm.nih.gov/omim/>) confirmed that many of the genes have been reported to be highly related to cancer development. For example, BCL2 is known to be one of the strongest predictors of shorter overall survival among patients was also reported to be a prognostic marker for breast cancer by Van't Veer *et al.*, (2002). Another example is the STK12 gene, which is located in a region frequently deleted in tumors and which contains tumor-related genes such as p53 (Tatsuka *et al.*, 1998).

Table 2: **Variable selection.** Table shows the significant variables (FDR = 10%) for the CPH-TREE, WEI-TREE, and AFT-TREE survival ensemble model. *a* indicates genes related to cancer phenotype. *b* indicates genes related to breast cancer phenotype.

CPH-TREE		WEI-TREE		AFT-TREE	
GenBank ID	Symbol	GenBank ID	Symbol	GenBank ID	Symbol
U96131	TRIP13	AL049265	IL6ST <sup>a</sup>	D43950	CCT5
AA453656	SUSD3	NM000633	BCL2 <sup>a</sup>	NM005733	KIF20A <sup>a</sup>
NM004217	STK12 <sup>a</sup>	NM005689	ABCB6	NM000633	BCL2 <sup>a</sup>
NM004456	EZH2 <sup>a</sup>	D25328	PFKP	AL157502	RGS5 <sup>a</sup>
NM014865	NCAPD2	NM017522	LRP8	AI810244	RILPL2
NM006763	BTG2 <sup>b</sup>	NM007057	ZWINT	NM014272	ADAMTS7
AL137718	DIAPH3	AB007916	RP11345P4.4	NM003430	ZNF91
NM014454	SESN1 <sup>a</sup>			NM002808	PSMD2
NM006460	HEXIM1			NM014321	ORC6L
				NM004553	NDUFS6
				NM006399	BATF <sup>a</sup>

## 2.2 Brain Tumor Data

In this section, we show a summary of the results for the brain tumor data (Table 3).

Table 3: Quartiles of the performance measures applied to the test sets of 50 random splits of the brain tumor data. **BS** stands for Brier score,  $R^2$  for coefficient of determination, and **CI** for Concordance Index. The top 3 best methods in each performance measure are identified by an asterisk.

Method	BS(50%)	BS(25%,75%)	$R^2$ (50%)	$R^2$ (25%,75%)	CI(50%)	CI(25%,75%)
AFT	0.116	[0.066,0.150]	0.203	[0.162,0.267]	0.615*	[0.571,0.669]
WEI	0.103*	[0.071,0.133]	0.178	[0.104,0.284]	0.609	[0.541,0.668]
CPH	0.129	[0.101,0.167]	0.198	[0.092,0.268]	0.615	[0.562,0.661]
CPH-L1	0.126	[0.077,0.172]	0.190	[0.080,0.295]	0.605	[0.574,0.642]
CPH-L2	0.111*	[0.066,0.156]	0.192	[0.135,0.292]	0.594	[0.548,0.651]
Bagging	0.102*	[0.065,0.162]	0.193	[0.128,0.266]	0.601	[0.556,0.657]
RF	0.116	[0.086,0.140]	0.214*	[0.120,0.265]	0.614*	[0.543,0.673]
RSF	0.123	[0.059,0.164]	0.212	[0.129,0.279]	0.609	[0.551,0.664]
CoxBoost	0.119	[0.089,0.158]	0.218*	[0.132,0.277]	0.602	[0.538,0.691]
AFT-TREE	0.121	[0.069,0.154]	0.212	[0.115,0.286]	0.618*	[0.576,0.671]
WEI-TREE	0.113	[0.073,0.158]	0.180	[0.100,0.282]	0.608	[0.568,0.666]
CPH-TREE	0.130	[0.074,0.153]	0.218*	[0.102,0.287]	0.611	[0.549,0.669]

### 3 Simulation study

We simulated data using a slightly modified version from Chipman *et al.* (2010). Like those authors, we used the Friedman’s Five Dimensional Test function to generate intricate interactions between 5 covariates. In addition to their strategy, however, we generated 20 more covariates ranging from small to big linear effect sizes, thus a total of 25 relevant covariates. Specifically, the covariate effects were constructed by simulating values of  $x = (x_1, x_2, \dots, x_p)$ , where  $x_1, x_2, \dots, x_p$  are iid  $\text{Uniform}(0, 3)$ , and  $y$  given  $x$  where  $y = f(x) + \epsilon = 10 \sin(\pi x_1 x_2) + 20(x_3 - 0.5)^2 + 10x_4 + 5x_5 + \beta \mathbf{x}_{6, \dots, 25} + \epsilon$  where  $\beta$  is a vector of size 20 with values drawn from uniform  $\mathbf{U}(-10, -1)$  and  $\mathbf{U}(1, 10)$  distributions and  $\epsilon$  is draw from a  $N(0, 1)$ . Because  $y$  only depends on  $x_1, \dots, x_{25}$ , the predictors  $x_{26}, \dots, x_p$  are irrelevant. These added variables together with the interactions and nonlinearities make it more challenging to find  $f(x)$  by standard parametric methods. We used the generated covariate effects  $y$  to obtain the log of survival times  $\log(t_i)$  using AFT, Weibull, and CPH as underlying survival models via the following identities: for AFT  $\log(t_i) = \alpha + y$  with  $\alpha = 3$ , for Weibull  $\log(t_i) = \exp(\exp((-\log(U(0, 1)) \times \exp(-y))^{(1/\tau)}))$  where  $\tau = 10$ , and for CPH  $\log(t_i) = \exp(\exp((-1/\lambda) \times \log(U(0, 1)) \times \exp(-y))^{(1/\tau)})$  where  $\lambda = 0.5$  and  $\tau = 20$  (Klein & Moeschberger, 1997).

We use the above setup with  $p = 200$  and various sample sizes (30, 70, 100, 200) with different proportions (20%, 40%, 70%) of randomly censored observations at time  $c_i \sim U(0, \log(t_i))$ . Thus for each observation, we generate  $[x_i, \min(\log(t_i), \log(c_i)), d_i]$ , where  $d_i$  is the event indicator. We compare the performance of our 3 proposed methods (AFT-TREE, WEI-TREE, CPH-TREE), using  $\text{ntree} = 20$  and 5,000 MCMC draws of  $f(x)$  after skipping 5000 burn-in iterations, against 9 other popular survival methods: multivariable linear AFT, Weibull, and Cox Prop Hazards models (AFT, WEI, CPH), conditional inference tree models as Bagging, Random Forest ( $\text{ntree} = 100$ ; Hothorn *et al.*, 2006), and Survival Random Forest ( $\text{ntree} = 2000$ ; Ishwaran *et al.*, 2008), L1 ( $\lambda_1 = 1$ ; Tibshirani, 1997) and L2 ( $\lambda_2 = 30$ ; Gui & Li, 2005) penalized version of Cox regression model (CPH-L1 and CPH-L2) and CoxBoost (Binder & Schumacher, 2009). We simulated 50 different data sets for each combination of sample size, proportion of censoring, and underlying model and then, we used 2/3 of the data to build the predictive model (training set) and applied the model and checked their performances in the remaining 1/3 of data (test set). Censored observations were balanced in each split. We assessed the performance of our method with 3 measures of predictive performance, the

Brier score (BS – Graf *et al.*, 1999), the coefficient of determination ( $R^2$ ) for the predictor (see van Wieringen *et al.*, 2009), and the Concordance Index (CI) available in the *Hmisc* R-package.

Performance results from our simulation experiment are shown in Tables from 4 to 12 and are summarized as follows:

1. The performance of our methods is sensitive to the choice of the underlying model used to generate the data with CPH methods performing better when the data is generated by a Cox model. This is also true for AFT and Weibull models.
2. Firstly, BS is the performance measure where our proposed models do better. Our method appears quite often in the top 3 ranks along with CPH-L2 and CoxBoost methods. Secondly, our method very frequently appears as top ranked in the CI along with the CPH-L2 and another tree based model, Bagging. Finally, our methods rarely figure in the top 3 best methods when using  $R^2$  measure, however it is quite similar to the measures obtained for the top 3 models: CPH-L1, CPH-L2, and CoxBoost.
3. For the BS, our method presents better performance when the percentage of censoring increases. We did not notice any pattern with respect to censoring in the other 2 performance measures.
4. Our proposed methods perform better in the BS and CI when the sample size is small.
5. We conclude that the simulation results fairly depict that our proposed procedures provide better or at least equivalent fit to the data as compared to competing methods.

In addition, we assess how the models were able to perform variable selection (Tables 13 to 15). Since there are 25 relevant covariates, we compared the top 25 most important covariates selected by each model/split and calculated the average and 95% CI for the True Positive Rate. Specifically, we used the p-value of univariate models to rank and then select the top covariates for the linear versions of AFT, Weibull, and CPH model. For the CPH-L1, CPH-L2, and CoxBoost models we used the absolute values of the estimated loadings ( $\hat{\beta}$ ) vector to rank and then select the top covariates. For the previous 6 models, only covariates with  $\hat{\beta} \neq 0$  were accounted for the TP calculation. Likewise, for the tree-based models (Bagging, RF, RSF, AFT-TREE, WEI-TREE, CPH-TREE) we rank the covariates based on their importance, i.e. relative frequencies of occurrence of a variable in the final model and compare with the true relevant covariates. Since we tried to simulate microarray



data sets as realistic as possible, the data we generated is very noisy. This characteristic of the data clearly affects the TPR based on the variable selection criteria that we used here because only the covariates with very strong effects will be always selected every time the model is build and, as a result, the best methods had maximums of TPR calculated at 55% (Tables 15, 16, 17). We summarize our findings regarding variable selection as follows:

1. Our proposed method, especially the WEI-TREE version, is always top ranked as the method with one of the highest TPR, along with CoxBoost and CPH-L2 methods. Although the AFT-TREE and CPH-TREE version rarely figure in the top 3 variable selection methods, they perform very well and can be considered strong competitors.
2. The TPR is usually higher for all evaluated method when the percentage of censored samples is small.
3. We did not notice any clear pattern change with respect to number of samples or underlying method used to generate the data.

Table 4: Brier score (BS) and inter-quartile region for data generated by the CPH model. Top 3 methods in each row are marked with an asterisk.

N	C (%)	AftLinear		WeiLinear		CphLinear		CphL1		CphL2		Bagging	
		BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)
30	20	0.137	[0.131,0.144]	0.133	[0.126,0.142]	0.168	[0.152,0.181]	0.137	[0.118,0.158]	0.119*	[0.101,0.140]	0.124	[0.108,0.137]
	40	0.125	[0.115,0.138]	0.124	[0.109,0.144]	0.150	[0.142,0.166]	0.137	[0.124,0.150]	0.088*	[0.075,0.097]	0.100*	[0.074,0.116]
	70	0.146	[0.126,0.155]	0.154	[0.126,0.176]	0.168	[0.155,0.193]	0.128	[0.118,0.143]	0.080*	[0.070,0.089]	0.131	[0.113,0.154]
70	20	0.168	[0.158,0.188]	0.140	[0.129,0.146]	0.136	[0.123,0.149]	0.120	[0.114,0.132]	0.115	[0.107,0.125]	0.126	[0.111,0.144]
	40	0.144	[0.131,0.151]	0.149	[0.140,0.166]	0.153	[0.138,0.164]	0.100*	[0.080,0.134]	0.099*	[0.089,0.109]	0.142	[0.130,0.163]
	70	0.157	[0.143,0.172]	0.135	[0.127,0.147]	0.152	[0.145,0.164]	0.109*	[0.098,0.125]	0.114	[0.093,0.128]	0.117	[0.107,0.126]
100	20	0.150	[0.137,0.158]	0.147	[0.136,0.166]	0.152	[0.133,0.172]	0.116*	[0.095,0.133]	0.077*	[0.067,0.092]	0.132	[0.106,0.149]
	40	0.148	[0.135,0.161]	0.139	[0.099,0.160]	0.125	[0.119,0.138]	0.129	[0.118,0.145]	0.095*	[0.088,0.105]	0.142	[0.126,0.149]
	70	0.131	[0.110,0.144]	0.145	[0.132,0.171]	0.136	[0.124,0.160]	0.117	[0.101,0.130]	0.098*	[0.083,0.112]	0.131	[0.115,0.136]
200	20	0.156	[0.148,0.168]	0.157	[0.127,0.187]	0.153	[0.145,0.176]	0.125	[0.116,0.135]	0.086*	[0.077,0.096]	0.092*	[0.076,0.120]
	40	0.164	[0.152,0.174]	0.131	[0.123,0.143]	0.134	[0.119,0.156]	0.139	[0.130,0.153]	0.108*	[0.085,0.121]	0.095*	[0.061,0.113]
	70	0.158	[0.132,0.201]	0.129	[0.112,0.136]	0.157	[0.144,0.171]	0.132	[0.113,0.157]	0.100*	[0.094,0.111]	0.096*	[0.085,0.109]
N	C (%)	RF		RSF		CoxBoost		AftTree		WeiTree		CphTree	
		BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)
30	20	0.113	[0.103,0.125]	0.145	[0.122,0.158]	0.105*	[0.096,0.116]	0.140	[0.124,0.159]	0.110*	[0.099,0.118]	0.120	[0.109,0.130]
	40	0.131	[0.117,0.177]	0.157	[0.146,0.166]	0.116	[0.090,0.132]	0.119	[0.099,0.127]	0.108	[0.093,0.128]	0.100*	[0.090,0.124]
	70	0.137	[0.126,0.158]	0.173	[0.158,0.180]	0.105*	[0.097,0.109]	0.134	[0.118,0.158]	0.108*	[0.092,0.118]	0.113	[0.101,0.123]
70	20	0.135	[0.122,0.147]	0.151	[0.130,0.166]	0.095*	[0.087,0.104]	0.132	[0.118,0.152]	0.095*	[0.087,0.106]	0.114*	[0.100,0.125]
	40	0.142	[0.135,0.151]	0.166	[0.157,0.176]	0.104*	[0.096,0.113]	0.127	[0.114,0.134]	0.146	[0.137,0.153]	0.114	[0.101,0.132]
	70	0.120	[0.103,0.139]	0.165	[0.157,0.174]	0.092*	[0.086,0.105]	0.117	[0.103,0.135]	0.098*	[0.083,0.114]	0.119	[0.107,0.139]
100	20	0.144	[0.133,0.158]	0.156	[0.146,0.167]	0.111*	[0.099,0.129]	0.129	[0.102,0.144]	0.130	[0.121,0.145]	0.134	[0.119,0.143]
	40	0.120	[0.108,0.128]	0.153	[0.142,0.167]	0.107*	[0.090,0.115]	0.107*	[0.099,0.125]	0.117	[0.100,0.121]	0.118	[0.108,0.133]
	70	0.126	[0.113,0.140]	0.161	[0.144,0.184]	0.084*	[0.074,0.099]	0.112	[0.103,0.123]	0.095*	[0.073,0.125]	0.109	[0.102,0.119]
200	20	0.125	[0.113,0.139]	0.135	[0.109,0.161]	0.116	[0.101,0.134]	0.108	[0.099,0.118]	0.149	[0.139,0.157]	0.107*	[0.086,0.116]
	40	0.148	[0.134,0.161]	0.159	[0.149,0.167]	0.086*	[0.080,0.096]	0.130	[0.115,0.153]	0.111	[0.097,0.125]	0.155	[0.124,0.165]
	70	0.120	[0.098,0.131]	0.163	[0.151,0.184]	0.099*	[0.085,0.106]	0.143	[0.118,0.172]	0.123	[0.113,0.131]	0.128	[0.115,0.144]

Table 5: Coefficient of determination ( $R^2$ ) and inter-quartile region for data generated by the CPH model. Top 3 methods in each row are marked with an asterisk.

N	C(%)	AftLinear $R^2$	$R^2$ (25%,75%)	WeiLinear $R^2$	$R^2$ (25%,75%)	CphLinear $R^2$	$R^2$ (25%,75%)	CphL1 $R^2$	$R^2$ (25%,75%)	CphL2 $R^2$	$R^2$ (25%,75%)	Bagging $R^2$	$R^2$ (25%,75%)
30	20	0.035	[0.023,0.051]	0.013	[0.007,0.021]	0.083	[0.079,0.104]	0.297*	[0.279,0.329]	0.327*	[0.317,0.335]	0.069	[0.057,0.078]
	40	0.033	[0.017,0.051]	0.011	[0.005,0.023]	0.079	[0.055,0.102]	0.327*	[0.316,0.336]	0.308*	[0.300,0.323]	0.027	[0.015,0.042]
	70	0.073	[0.057,0.084]	0.030	[0.014,0.045]	0.066	[0.052,0.086]	0.339*	[0.332,0.355]	0.320*	[0.307,0.338]	0.052	[0.039,0.061]
70	20	0.048	[0.039,0.059]	0.022	[0.007,0.051]	0.065	[0.052,0.078]	0.308*	[0.292,0.319]	0.309*	[0.296,0.328]	0.036	[0.030,0.054]
	40	0.056	[0.048,0.064]	0.009	[0.005,0.015]	0.090	[0.081,0.100]	0.331*	[0.322,0.338]	0.324*	[0.312,0.334]	0.040	[0.027,0.050]
	70	0.026	[0.010,0.050]	0.007	[0.004,0.016]	0.095	[0.085,0.103]	0.320*	[0.309,0.334]	0.321*	[0.311,0.329]	0.041	[0.032,0.050]
100	20	0.057	[0.045,0.066]	0.008	[0.005,0.017]	0.072	[0.051,0.094]	0.328*	[0.317,0.339]	0.347*	[0.315,0.374]	0.055	[0.028,0.074]
	40	0.062	[0.053,0.075]	0.019	[0.008,0.024]	0.088	[0.075,0.097]	0.327*	[0.312,0.343]	0.335*	[0.322,0.342]	0.056	[0.047,0.070]
	70	0.026	[0.012,0.056]	0.013	[0.007,0.023]	0.127	[0.106,0.134]	0.335*	[0.325,0.355]	0.309*	[0.296,0.316]	0.076	[0.032,0.086]
200	20	0.028	[0.015,0.049]	0.014	[0.006,0.024]	0.109	[0.087,0.121]	0.334*	[0.326,0.350]	0.287*	[0.278,0.305]	0.047	[0.028,0.055]
	40	0.034	[0.012,0.047]	0.019	[0.009,0.035]	0.077	[0.054,0.097]	0.302*	[0.285,0.320]	0.293*	[0.277,0.316]	0.047	[0.034,0.056]
	70	0.056	[0.046,0.079]	0.012	[0.005,0.023]	0.103	[0.092,0.117]	0.322*	[0.311,0.338]	0.341*	[0.327,0.360]	0.036	[0.025,0.045]
N	C(%)	RF $R^2$	$R^2$ (25%,75%)	RSF $R^2$	$R^2$ (25%,75%)	CoxBoost $R^2$	$R^2$ (25%,75%)	AftTree $R^2$	$R^2$ (25%,75%)	WeiTree $R^2$	$R^2$ (25%,75%)	CphTree $R^2$	$R^2$ (25%,75%)
30	20	0.285	[0.279,0.294]	0.238	[0.227,0.262]	0.327*	[0.319,0.334]	0.283	[0.274,0.293]	0.268	[0.256,0.278]	0.290	[0.278,0.306]
	40	0.266	[0.256,0.292]	0.248	[0.237,0.260]	0.332*	[0.310,0.344]	0.284	[0.271,0.302]	0.261	[0.237,0.278]	0.283	[0.272,0.298]
	70	0.301	[0.282,0.319]	0.243	[0.223,0.255]	0.328*	[0.312,0.341]	0.279	[0.263,0.291]	0.254	[0.245,0.266]	0.287	[0.280,0.294]
70	20	0.295	[0.285,0.309]	0.224	[0.208,0.235]	0.317*	[0.301,0.329]	0.293	[0.280,0.304]	0.264	[0.258,0.276]	0.290	[0.279,0.311]
	40	0.292	[0.274,0.307]	0.236	[0.223,0.251]	0.312*	[0.298,0.325]	0.297	[0.260,0.323]	0.251	[0.240,0.270]	0.296	[0.282,0.308]
	70	0.299	[0.282,0.318]	0.228	[0.220,0.238]	0.335*	[0.322,0.354]	0.286	[0.273,0.298]	0.286	[0.260,0.313]	0.285	[0.280,0.291]
100	20	0.259	[0.246,0.280]	0.232	[0.226,0.238]	0.319*	[0.308,0.329]	0.271	[0.266,0.280]	0.258	[0.246,0.270]	0.319	[0.298,0.337]
	40	0.267	[0.238,0.298]	0.240	[0.227,0.248]	0.339*	[0.320,0.358]	0.266	[0.249,0.282]	0.249	[0.235,0.260]	0.284	[0.271,0.298]
	70	0.297	[0.283,0.313]	0.237	[0.227,0.250]	0.306	[0.281,0.328]	0.284	[0.278,0.295]	0.263	[0.228,0.275]	0.311*	[0.294,0.344]
200	20	0.280	[0.269,0.291]	0.252	[0.233,0.271]	0.361*	[0.324,0.382]	0.280	[0.269,0.286]	0.273	[0.259,0.287]	0.285	[0.268,0.298]
	40	0.282	[0.265,0.303]	0.223	[0.212,0.236]	0.329*	[0.317,0.338]	0.278	[0.269,0.289]	0.263	[0.249,0.274]	0.289	[0.281,0.296]
	70	0.300	[0.284,0.311]	0.245	[0.232,0.260]	0.336*	[0.324,0.347]	0.280	[0.273,0.293]	0.249	[0.238,0.265]	0.284	[0.272,0.300]

Table 6: Concordance index(CI) and inter-quartile region for data generated by the CPH model.  
 Top 3 methods in each row are marked with an asterisk.

N	C (%)	AftLinear		WeiLinear		CphLinear		CphL1		CphL2		Bagging	
		CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)
30	20	0.589	[0.575,0.603]	0.591	[0.582,0.602]	0.540	[0.535,0.547]	0.667*	[0.655,0.675]	0.566	[0.548,0.597]	0.663*	[0.645,0.674]
	40	0.614	[0.589,0.633]	0.601	[0.582,0.611]	0.549	[0.541,0.560]	0.659*	[0.642,0.668]	0.555	[0.546,0.564]	0.625	[0.613,0.638]
	70	0.583	[0.567,0.597]	0.611	[0.588,0.635]	0.563	[0.550,0.575]	0.692*	[0.658,0.722]	0.560	[0.545,0.567]	0.646*	[0.636,0.660]
70	20	0.586	[0.572,0.612]	0.581	[0.563,0.600]	0.545	[0.537,0.554]	0.665*	[0.655,0.679]	0.582	[0.561,0.609]	0.639*	[0.626,0.646]
	40	0.622	[0.612,0.634]	0.593	[0.579,0.605]	0.534	[0.519,0.554]	0.660*	[0.652,0.676]	0.550	[0.539,0.564]	0.649*	[0.626,0.672]
	70	0.592	[0.583,0.603]	0.580	[0.570,0.594]	0.551	[0.540,0.569]	0.679*	[0.668,0.690]	0.569	[0.551,0.590]	0.641*	[0.627,0.655]
100	20	0.612	[0.594,0.645]	0.597	[0.581,0.604]	0.531	[0.512,0.548]	0.661*	[0.648,0.682]	0.573	[0.560,0.582]	0.634*	[0.624,0.653]
	40	0.598	[0.582,0.605]	0.592	[0.583,0.603]	0.548	[0.538,0.573]	0.693*	[0.676,0.712]	0.556	[0.541,0.566]	0.638	[0.627,0.665]
	70	0.590	[0.579,0.600]	0.609	[0.592,0.631]	0.513	[0.506,0.522]	0.681*	[0.667,0.695]	0.554	[0.544,0.563]	0.669*	[0.655,0.688]
200	20	0.610	[0.600,0.622]	0.613	[0.602,0.625]	0.529	[0.524,0.541]	0.650*	[0.629,0.685]	0.545	[0.535,0.560]	0.637	[0.626,0.649]
	40	0.604	[0.594,0.620]	0.591	[0.581,0.600]	0.526	[0.516,0.538]	0.662*	[0.653,0.670]	0.558	[0.543,0.571]	0.616	[0.607,0.626]
	70	0.591	[0.582,0.603]	0.612	[0.600,0.626]	0.549	[0.534,0.561]	0.680*	[0.669,0.691]	0.586	[0.571,0.599]	0.653*	[0.634,0.663]
N	C (%)	RF		RSF		CoxBoost		AftTree		WeiTree		CphTree	
		CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)
30	20	0.648	[0.618,0.671]	0.592	[0.584,0.602]	0.575	[0.566,0.586]	0.617	[0.603,0.625]	0.617	[0.601,0.640]	0.681*	[0.664,0.708]
	40	0.622	[0.609,0.629]	0.568	[0.554,0.585]	0.579	[0.570,0.591]	0.605	[0.596,0.614]	0.645*	[0.630,0.656]	0.678*	[0.670,0.686]
	70	0.612	[0.601,0.620]	0.566	[0.553,0.586]	0.599	[0.590,0.608]	0.625	[0.608,0.638]	0.636	[0.622,0.665]	0.674*	[0.664,0.688]
70	20	0.623	[0.609,0.637]	0.583	[0.575,0.591]	0.587	[0.568,0.604]	0.608	[0.596,0.620]	0.622	[0.595,0.636]	0.688*	[0.669,0.704]
	40	0.613	[0.597,0.624]	0.567	[0.551,0.588]	0.600	[0.585,0.632]	0.609	[0.600,0.620]	0.619	[0.610,0.627]	0.711*	[0.697,0.721]
	70	0.623	[0.609,0.633]	0.582	[0.572,0.589]	0.609	[0.600,0.622]	0.599	[0.585,0.615]	0.624	[0.616,0.631]	0.699*	[0.684,0.709]
100	20	0.607	[0.583,0.638]	0.594	[0.583,0.611]	0.601	[0.588,0.614]	0.591	[0.582,0.603]	0.607	[0.588,0.627]	0.675*	[0.669,0.689]
	40	0.599	[0.582,0.619]	0.586	[0.580,0.601]	0.591	[0.584,0.605]	0.596	[0.586,0.607]	0.657*	[0.641,0.677]	0.702*	[0.689,0.712]
	70	0.607	[0.598,0.632]	0.557	[0.542,0.579]	0.589	[0.580,0.598]	0.599	[0.586,0.611]	0.617	[0.602,0.629]	0.700*	[0.689,0.708]
200	20	0.640*	[0.630,0.653]	0.590	[0.576,0.599]	0.569	[0.561,0.577]	0.600	[0.591,0.612]	0.621	[0.606,0.644]	0.684*	[0.675,0.696]
	40	0.610	[0.596,0.620]	0.577	[0.562,0.604]	0.597	[0.587,0.608]	0.600	[0.587,0.615]	0.646*	[0.636,0.662]	0.682*	[0.662,0.698]
	70	0.606	[0.575,0.628]	0.555	[0.540,0.568]	0.611	[0.601,0.626]	0.594	[0.584,0.600]	0.649	[0.633,0.672]	0.688*	[0.669,0.701]

Table 7: Brier score (BS) and inter-quartile region for data generated by the Weibull model. Top 3 methods in each row are marked with an asterisk.

N	C (%)	AftLinear		WeibLinear		CphLinear		CphL1		CphL2		Bagging	
		BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)
30	20	0.151	[0.145,0.158]	0.152	[0.125,0.187]	0.125	[0.098,0.150]	0.108	[0.087,0.123]	0.114	[0.103,0.134]	0.082*	[0.068,0.105]
	40	0.156	[0.146,0.169]	0.153	[0.145,0.166]	0.146	[0.135,0.157]	0.110	[0.100,0.121]	0.081*	[0.065,0.102]	0.122	[0.103,0.145]
	70	0.161	[0.148,0.183]	0.129	[0.101,0.144]	0.160	[0.152,0.174]	0.130	[0.116,0.144]	0.084*	[0.073,0.096]	0.127	[0.117,0.135]
70	20	0.159	[0.150,0.175]	0.128	[0.116,0.137]	0.149	[0.141,0.156]	0.117	[0.107,0.130]	0.093*	[0.080,0.103]	0.122	[0.110,0.145]
	40	0.176	[0.160,0.189]	0.128	[0.122,0.137]	0.159	[0.149,0.170]	0.137	[0.124,0.154]	0.112	[0.101,0.127]	0.115	[0.101,0.127]
	70	0.126	[0.110,0.149]	0.149	[0.134,0.159]	0.141	[0.129,0.158]	0.106*	[0.090,0.119]	0.097*	[0.089,0.110]	0.127	[0.113,0.146]
100	20	0.131	[0.107,0.158]	0.165	[0.141,0.186]	0.130	[0.119,0.139]	0.123	[0.111,0.137]	0.104*	[0.077,0.120]	0.120	[0.098,0.132]
	40	0.145	[0.129,0.162]	0.140	[0.132,0.151]	0.156	[0.149,0.172]	0.135	[0.127,0.144]	0.108*	[0.095,0.126]	0.141	[0.102,0.156]
	70	0.130	[0.115,0.149]	0.152	[0.141,0.164]	0.132	[0.109,0.145]	0.134	[0.120,0.145]	0.115	[0.100,0.123]	0.113	[0.099,0.126]
200	20	0.148	[0.139,0.155]	0.146	[0.131,0.167]	0.156	[0.136,0.170]	0.125	[0.112,0.133]	0.108	[0.093,0.117]	0.110	[0.091,0.130]
	40	0.166	[0.151,0.187]	0.143	[0.131,0.162]	0.132	[0.097,0.152]	0.121	[0.110,0.135]	0.089*	[0.075,0.108]	0.103*	[0.091,0.116]
	70	0.149	[0.142,0.160]	0.142	[0.133,0.149]	0.142	[0.136,0.149]	0.138	[0.124,0.146]	0.085*	[0.063,0.094]	0.142	[0.123,0.172]
N	C (%)	RF		RSF		CoxBoost		AftTree		WeiTree		CphTree	
		BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)
30	20	0.098*	[0.085,0.111]	0.171	[0.160,0.181]	0.111	[0.094,0.126]	0.117	[0.094,0.125]	0.089*	[0.073,0.098]	0.099	[0.074,0.109]
	40	0.133	[0.112,0.139]	0.173	[0.161,0.187]	0.102*	[0.095,0.110]	0.122	[0.112,0.136]	0.066*	[0.060,0.080]	0.120	[0.112,0.130]
	70	0.140	[0.127,0.152]	0.153	[0.137,0.160]	0.091*	[0.080,0.101]	0.127	[0.115,0.139]	0.077*	[0.054,0.094]	0.099	[0.079,0.120]
70	20	0.112*	[0.106,0.125]	0.184	[0.172,0.194]	0.118	[0.107,0.128]	0.116	[0.108,0.141]	0.078*	[0.053,0.094]	0.140	[0.123,0.155]
	40	0.126	[0.116,0.140]	0.140	[0.118,0.178]	0.104*	[0.095,0.125]	0.122	[0.109,0.132]	0.072*	[0.057,0.089]	0.102*	[0.092,0.114]
	70	0.123	[0.114,0.135]	0.136	[0.110,0.160]	0.115	[0.102,0.127]	0.113	[0.099,0.124]	0.112*	[0.101,0.122]	0.138	[0.099,0.174]
100	20	0.131	[0.118,0.144]	0.157	[0.147,0.168]	0.108	[0.086,0.121]	0.091*	[0.075,0.120]	0.075*	[0.060,0.084]	0.138	[0.123,0.152]
	40	0.142	[0.135,0.156]	0.152	[0.128,0.165]	0.101*	[0.088,0.117]	0.126	[0.116,0.140]	0.117	[0.088,0.125]	0.116*	[0.106,0.122]
	70	0.123	[0.110,0.129]	0.150	[0.137,0.159]	0.103*	[0.092,0.115]	0.095*	[0.078,0.111]	0.102*	[0.088,0.109]	0.143	[0.121,0.156]
200	20	0.142	[0.119,0.171]	0.173	[0.158,0.192]	0.107*	[0.100,0.118]	0.109	[0.086,0.130]	0.073*	[0.059,0.084]	0.105*	[0.100,0.114]
	40	0.130	[0.108,0.147]	0.140	[0.131,0.158]	0.101*	[0.090,0.113]	0.133	[0.119,0.145]	0.108	[0.095,0.119]	0.131	[0.119,0.144]
	70	0.131	[0.114,0.148]	0.152	[0.136,0.169]	0.089*	[0.075,0.100]	0.118	[0.108,0.129]	0.114*	[0.103,0.124]	0.128	[0.118,0.137]

Table 8: Coefficient of determination ( $R^2$ ) and inter-quartile region for data generated by the Weibull model. Top 3 methods in each row are marked with an asterisk.

N	C(%)	AftLinear $R^2$	$R^2$ (25%,75%)	WeiLinear $R^2$	$R^2$ (25%,75%)	CphLinear $R^2$	$R^2$ (25%,75%)	CphL1 $R^2$	$R^2$ (25%,75%)	CphL2 $R^2$	$R^2$ (25%,75%)	Bagging $R^2$	$R^2$ (25%,75%)	
30	20	0.032	[0.023,0.040]	0.018	[0.010,0.024]	0.097	[0.087,0.111]	0.322*	[0.298,0.336]	0.336*	[0.326,0.348]	0.037	[0.012,0.065]	
	40	0.061	[0.046,0.079]	0.021	[0.007,0.036]	0.099	[0.089,0.107]	0.307	[0.295,0.334]	0.307*	[0.298,0.320]	0.063	[0.056,0.067]	
	70	0.031	[0.017,0.045]	0.013	[0.008,0.022]	0.089	[0.080,0.103]	0.326*	[0.311,0.337]	0.324*	[0.314,0.333]	0.037	[0.026,0.044]	
70	20	0.048	[0.039,0.063]	0.009	[0.004,0.015]	0.095	[0.088,0.104]	0.315*	[0.302,0.325]	0.341*	[0.323,0.356]	0.060	[0.050,0.073]	
	40	0.030	[0.007,0.046]	0.023	[0.012,0.036]	0.106	[0.092,0.119]	0.333*	[0.322,0.341]	0.330*	[0.323,0.337]	0.038	[0.024,0.049]	
	70	0.067	[0.057,0.074]	0.009	[0.004,0.017]	0.087	[0.079,0.095]	0.340*	[0.328,0.351]	0.331*	[0.322,0.340]	0.039	[0.026,0.051]	
100	20	0.056	[0.043,0.064]	0.018	[0.007,0.027]	0.094	[0.083,0.101]	0.336*	[0.325,0.350]	0.316	[0.309,0.329]	0.045	[0.020,0.064]	
	40	0.059	[0.051,0.069]	0.021	[0.008,0.048]	0.078	[0.068,0.098]	0.343*	[0.330,0.357]	0.335*	[0.322,0.348]	0.054	[0.037,0.072]	
	70	0.045	[0.022,0.070]	0.010	[0.005,0.022]	0.100	[0.089,0.111]	0.322*	[0.296,0.340]	0.341*	[0.331,0.356]	0.047	[0.038,0.054]	
200	20	0.018	[0.009,0.039]	0.011	[0.005,0.019]	0.071	[0.053,0.080]	0.346*	[0.319,0.361]	0.307*	[0.298,0.320]	0.031	[0.015,0.051]	
	40	0.058	[0.047,0.069]	0.015	[0.009,0.024]	0.107	[0.100,0.116]	0.340*	[0.324,0.349]	0.313	[0.298,0.327]	0.030	[0.018,0.045]	
	70	0.057	[0.045,0.075]	0.018	[0.009,0.033]	0.079	[0.066,0.097]	0.322*	[0.311,0.340]	0.323*	[0.310,0.344]	0.047	[0.030,0.062]	
N	C(%)	RF	$R^2$ (25%,75%)	RSF	$R^2$ (25%,75%)	CoxBoost	$R^2$ (25%,75%)	AftTree	$R^2$ (25%,75%)	WeiTree	$R^2$ (25%,75%)	CphTree	$R^2$ (25%,75%)	
		30	0.295	[0.283,0.303]	0.246	[0.226,0.263]	0.309*	[0.299,0.324]	0.286	[0.271,0.297]	0.305	[0.298,0.325]	0.241	[0.232,0.254]
		40	0.290	[0.282,0.300]	0.247	[0.238,0.258]	0.330*	[0.318,0.347]	0.263	[0.235,0.285]	0.320*	[0.301,0.355]	0.256	[0.249,0.262]
70	20	0.281	[0.263,0.298]	0.260	[0.250,0.278]	0.336*	[0.327,0.347]	0.285	[0.274,0.300]	0.288	[0.272,0.302]	0.241	[0.223,0.277]	
	20	0.282	[0.271,0.296]	0.217	[0.199,0.233]	0.321*	[0.312,0.335]	0.301	[0.290,0.312]	0.293	[0.283,0.301]	0.262	[0.249,0.272]	
	40	0.292	[0.272,0.312]	0.228	[0.211,0.247]	0.327*	[0.318,0.343]	0.271	[0.262,0.280]	0.294	[0.284,0.302]	0.236	[0.219,0.258]	
100	20	0.272	[0.252,0.281]	0.211	[0.201,0.223]	0.318	[0.299,0.333]	0.294	[0.276,0.318]	0.319*	[0.299,0.344]	0.244	[0.213,0.261]	
	20	0.259	[0.244,0.283]	0.231	[0.216,0.243]	0.324*	[0.304,0.364]	0.270	[0.255,0.290]	0.317*	[0.303,0.327]	0.257	[0.245,0.272]	
	40	0.274	[0.264,0.284]	0.241	[0.232,0.247]	0.328*	[0.319,0.335]	0.293	[0.285,0.300]	0.291	[0.267,0.312]	0.247	[0.229,0.259]	
200	20	0.261	[0.252,0.276]	0.259	[0.244,0.270]	0.319*	[0.301,0.330]	0.268	[0.247,0.281]	0.311	[0.304,0.323]	0.248	[0.239,0.264]	
	20	0.272	[0.259,0.280]	0.221	[0.213,0.233]	0.322*	[0.314,0.341]	0.295	[0.265,0.336]	0.293	[0.278,0.304]	0.263	[0.256,0.272]	
	40	0.274	[0.253,0.282]	0.214	[0.206,0.230]	0.325*	[0.311,0.339]	0.273	[0.255,0.284]	0.320*	[0.310,0.331]	0.260	[0.250,0.266]	
70	0.264	[0.253,0.272]	0.243	[0.227,0.256]	0.330*	[0.322,0.340]	0.289	[0.274,0.300]	0.297	[0.276,0.320]	0.264	[0.252,0.274]		

Table 9: Concordance index (CI) and inter-quartile region for data generated by the Weibull model. Top 3 methods in each row are marked with an asterisk.

N	C (%)	AftLinear		WeiLinear		CphLinear		CphL1		CphL2		Bagging	
		CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)
30	20	0.601	[0.592,0.620]	0.616	[0.600,0.627]	0.542	[0.526,0.557]	0.667*	[0.650,0.679]	0.563	[0.548,0.574]	0.636*	[0.622,0.640]
	40	0.596	[0.583,0.604]	0.602	[0.590,0.612]	0.524	[0.513,0.535]	0.693*	[0.682,0.702]	0.554	[0.544,0.566]	0.649*	[0.639,0.666]
	70	0.584	[0.570,0.599]	0.626	[0.608,0.635]	0.530	[0.515,0.549]	0.658*	[0.643,0.669]	0.552	[0.544,0.566]	0.653*	[0.643,0.669]
70	20	0.593	[0.583,0.600]	0.577	[0.565,0.593]	0.527	[0.511,0.539]	0.659*	[0.641,0.671]	0.570	[0.560,0.580]	0.617	[0.594,0.640]
	40	0.609	[0.601,0.621]	0.608	[0.598,0.629]	0.559	[0.548,0.567]	0.672*	[0.665,0.679]	0.545	[0.537,0.557]	0.634*	[0.622,0.646]
	70	0.587	[0.575,0.596]	0.597	[0.587,0.609]	0.524	[0.512,0.542]	0.666*	[0.655,0.671]	0.579	[0.552,0.596]	0.622	[0.613,0.639]
100	20	0.626	[0.607,0.650]	0.620	[0.605,0.639]	0.545	[0.533,0.562]	0.688*	[0.657,0.720]	0.545	[0.530,0.552]	0.627	[0.607,0.637]
	40	0.581	[0.559,0.603]	0.621	[0.604,0.628]	0.563	[0.539,0.573]	0.646*	[0.616,0.680]	0.581	[0.568,0.587]	0.638*	[0.628,0.646]
	70	0.576	[0.560,0.587]	0.609	[0.597,0.621]	0.564	[0.552,0.578]	0.666*	[0.645,0.683]	0.572	[0.559,0.582]	0.657*	[0.634,0.672]
200	20	0.626	[0.619,0.633]	0.596	[0.589,0.614]	0.512	[0.506,0.530]	0.645*	[0.623,0.680]	0.573	[0.558,0.592]	0.665*	[0.657,0.671]
	40	0.583	[0.568,0.594]	0.597	[0.584,0.612]	0.548	[0.538,0.560]	0.655*	[0.640,0.664]	0.578	[0.567,0.593]	0.629*	[0.617,0.656]
	70	0.598	[0.583,0.615]	0.578	[0.562,0.594]	0.542	[0.536,0.550]	0.679*	[0.660,0.698]	0.589	[0.567,0.606]	0.640*	[0.624,0.652]
N	C (%)	RF		RSF		CoxBoost		AftTree		WeiTree		CphTree	
		CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)
30	20	0.623	[0.618,0.631]	0.574	[0.562,0.585]	0.594	[0.584,0.604]	0.610	[0.601,0.616]	0.646*	[0.637,0.657]	0.616	[0.600,0.626]
	40	0.618	[0.601,0.628]	0.562	[0.545,0.574]	0.626	[0.608,0.637]	0.587	[0.576,0.601]	0.624	[0.610,0.631]	0.644*	[0.631,0.653]
	70	0.625	[0.608,0.644]	0.583	[0.569,0.593]	0.623	[0.595,0.646]	0.611	[0.603,0.618]	0.622	[0.614,0.637]	0.630*	[0.624,0.640]
70	20	0.613	[0.596,0.624]	0.576	[0.558,0.587]	0.615	[0.598,0.634]	0.579	[0.548,0.615]	0.646*	[0.614,0.658]	0.632*	[0.620,0.645]
	40	0.614	[0.605,0.621]	0.572	[0.560,0.581]	0.588	[0.575,0.600]	0.619	[0.601,0.648]	0.606	[0.595,0.621]	0.626*	[0.606,0.652]
	70	0.632*	[0.610,0.648]	0.602	[0.581,0.618]	0.604	[0.596,0.613]	0.607	[0.589,0.624]	0.625	[0.615,0.632]	0.651*	[0.633,0.667]
100	20	0.636*	[0.612,0.648]	0.562	[0.552,0.576]	0.600	[0.593,0.607]	0.624	[0.615,0.646]	0.625	[0.602,0.646]	0.646*	[0.631,0.660]
	40	0.624	[0.613,0.632]	0.568	[0.542,0.594]	0.617	[0.600,0.627]	0.614	[0.600,0.628]	0.630	[0.614,0.644]	0.634*	[0.625,0.643]
	70	0.630	[0.611,0.649]	0.579	[0.568,0.593]	0.592	[0.582,0.600]	0.615	[0.587,0.628]	0.636*	[0.630,0.645]	0.631	[0.619,0.652]
200	20	0.639	[0.617,0.652]	0.620	[0.598,0.631]	0.599	[0.584,0.608]	0.591	[0.580,0.605]	0.645*	[0.625,0.655]	0.636	[0.626,0.653]
	40	0.623*	[0.607,0.632]	0.587	[0.582,0.600]	0.593	[0.578,0.611]	0.620	[0.603,0.632]	0.617	[0.596,0.630]	0.622	[0.613,0.632]
	70	0.619	[0.612,0.627]	0.565	[0.537,0.582]	0.601	[0.585,0.614]	0.574	[0.552,0.595]	0.638*	[0.622,0.651]	0.607	[0.600,0.620]

Table 10: Brier score (BS) and inter-quartile region for data generated by the AFT model. Top 3 methods in each row are marked with an asterisk.

N	C (%)	AftLinear		WeiLinear		CphLinear		CphL1		CphL2		Bagging	
		BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)
30	20	0.144	[0.121,0.159]	0.138	[0.132,0.146]	0.157	[0.145,0.170]	0.120	[0.111,0.129]	0.113*	[0.099,0.126]	0.121	[0.106,0.130]
	40	0.149	[0.137,0.161]	0.152	[0.140,0.159]	0.145	[0.137,0.154]	0.133	[0.115,0.147]	0.084*	[0.071,0.101]	0.127	[0.114,0.138]
	70	0.143	[0.132,0.164]	0.145	[0.130,0.156]	0.146	[0.133,0.151]	0.131	[0.120,0.140]	0.101	[0.094,0.109]	0.096*	[0.087,0.113]
70	20	0.156	[0.142,0.172]	0.135	[0.125,0.146]	0.143	[0.129,0.152]	0.124	[0.106,0.133]	0.094*	[0.081,0.106]	0.102	[0.082,0.116]
	40	0.155	[0.147,0.167]	0.141	[0.129,0.155]	0.160	[0.146,0.181]	0.139	[0.122,0.154]	0.100*	[0.090,0.106]	0.108*	[0.096,0.123]
	70	0.149	[0.140,0.166]	0.127	[0.114,0.145]	0.162	[0.152,0.172]	0.116	[0.100,0.133]	0.101*	[0.086,0.116]	0.111*	[0.099,0.125]
100	20	0.159	[0.135,0.178]	0.141	[0.124,0.151]	0.147	[0.128,0.162]	0.122	[0.112,0.130]	0.105*	[0.095,0.116]	0.122	[0.116,0.132]
	40	0.144	[0.117,0.157]	0.160	[0.144,0.185]	0.139	[0.123,0.155]	0.111	[0.091,0.134]	0.106*	[0.097,0.115]	0.134	[0.119,0.142]
	70	0.153	[0.140,0.166]	0.152	[0.138,0.167]	0.164	[0.153,0.178]	0.139	[0.124,0.157]	0.096*	[0.082,0.102]	0.115	[0.102,0.133]
200	20	0.141	[0.132,0.148]	0.138	[0.126,0.156]	0.136	[0.125,0.148]	0.131	[0.118,0.142]	0.096*	[0.078,0.116]	0.121	[0.113,0.132]
	40	0.166	[0.149,0.185]	0.162	[0.153,0.168]	0.148	[0.140,0.156]	0.116	[0.103,0.126]	0.107*	[0.091,0.121]	0.110*	[0.104,0.129]
	70	0.156	[0.145,0.164]	0.158	[0.129,0.182]	0.150	[0.141,0.164]	0.130	[0.124,0.148]	0.111*	[0.094,0.122]	0.105*	[0.091,0.133]
N	C (%)	RF		RSF		CoxBoost		AftTree		WeiTree		CphTree	
		BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)	BS	BS(25%,75%)
30	20	0.129	[0.118,0.138]	0.151	[0.139,0.161]	0.097*	[0.088,0.103]	0.101*	[0.094,0.115]	0.134	[0.122,0.140]	0.130	[0.115,0.137]
	40	0.123	[0.114,0.137]	0.147	[0.138,0.157]	0.110	[0.101,0.123]	0.097*	[0.088,0.110]	0.125	[0.120,0.141]	0.108*	[0.094,0.123]
	70	0.117	[0.089,0.144]	0.144	[0.131,0.160]	0.088*	[0.076,0.101]	0.113*	[0.100,0.123]	0.136	[0.121,0.146]	0.114	[0.098,0.129]
70	20	0.124	[0.111,0.138]	0.171	[0.153,0.179]	0.101*	[0.092,0.110]	0.102*	[0.092,0.118]	0.136	[0.124,0.151]	0.107	[0.102,0.126]
	40	0.136	[0.126,0.151]	0.166	[0.155,0.178]	0.111	[0.100,0.122]	0.101*	[0.089,0.116]	0.122	[0.104,0.132]	0.128	[0.117,0.139]
	70	0.135	[0.120,0.145]	0.159	[0.148,0.164]	0.095*	[0.086,0.103]	0.120	[0.108,0.136]	0.132	[0.124,0.140]	0.122	[0.093,0.146]
100	20	0.120	[0.104,0.146]	0.158	[0.147,0.165]	0.111*	[0.101,0.130]	0.114*	[0.101,0.122]	0.123	[0.112,0.137]	0.125	[0.113,0.132]
	40	0.118	[0.090,0.142]	0.152	[0.141,0.161]	0.098*	[0.089,0.112]	0.121	[0.106,0.146]	0.103*	[0.091,0.121]	0.141	[0.132,0.151]
	70	0.132	[0.120,0.146]	0.142	[0.133,0.154]	0.094*	[0.080,0.103]	0.106*	[0.087,0.116]	0.107	[0.096,0.118]	0.131	[0.115,0.151]
200	20	0.101	[0.091,0.114]	0.137	[0.125,0.148]	0.111	[0.095,0.125]	0.109	[0.097,0.116]	0.107*	[0.094,0.117]	0.106*	[0.090,0.123]
	40	0.121	[0.107,0.127]	0.159	[0.148,0.197]	0.128	[0.113,0.136]	0.117	[0.108,0.132]	0.107*	[0.096,0.120]	0.125	[0.115,0.139]
	70	0.121	[0.100,0.131]	0.163	[0.148,0.187]	0.125	[0.112,0.142]	0.105*	[0.096,0.123]	0.120	[0.107,0.131]	0.130	[0.119,0.140]



Table 11: Coefficient of determination ( $R^2$ ) and inter-quartile region for data generated by the AFT model. Top 3 methods in each row are marked with an asterisk.

N	C (%)	AftLinear		WeiLinear		CphLinear		CphL1		CphL2		Bagging	
		$R^2$	$R^2(25\%,75\%)$	$R^2$	$R^2(25\%,75\%)$	$R^2$	$R^2(25\%,75\%)$	$R^2$	$R^2(25\%,75\%)$	$R^2$	$R^2(25\%,75\%)$	$R^2$	$R^2(25\%,75\%)$
30	20	0.055	[0.046,0.066]	0.012	[0.006,0.019]	0.092	[0.077,0.099]	0.326*	[0.318,0.336]	0.326*	[0.318,0.337]	0.038	[0.025,0.061]
	40	0.045	[0.031,0.055]	0.010	[0.005,0.019]	0.095	[0.090,0.108]	0.322*	[0.308,0.333]	0.319*	[0.307,0.326]	0.042	[0.029,0.049]
	70	0.056	[0.048,0.066]	0.012	[0.007,0.018]	0.110	[0.100,0.128]	0.337*	[0.319,0.350]	0.317*	[0.303,0.327]	0.023	[0.013,0.046]
70	20	0.040	[0.021,0.057]	0.018	[0.010,0.032]	0.103	[0.088,0.113]	0.335*	[0.322,0.342]	0.338*	[0.323,0.353]	0.040	[0.031,0.052]
	40	0.071	[0.059,0.078]	0.013	[0.005,0.024]	0.091	[0.075,0.099]	0.333*	[0.323,0.348]	0.302*	[0.277,0.326]	0.049	[0.033,0.067]
	70	0.055	[0.043,0.064]	0.012	[0.005,0.020]	0.096	[0.085,0.107]	0.338*	[0.311,0.368]	0.334*	[0.324,0.347]	0.047	[0.039,0.058]
100	20	0.045	[0.036,0.054]	0.012	[0.005,0.022]	0.082	[0.070,0.109]	0.302*	[0.288,0.320]	0.327*	[0.318,0.342]	0.059	[0.046,0.073]
	40	0.045	[0.035,0.050]	0.015	[0.007,0.020]	0.084	[0.077,0.096]	0.318*	[0.308,0.325]	0.315*	[0.302,0.326]	0.053	[0.044,0.064]
	70	0.046	[0.036,0.054]	0.012	[0.006,0.020]	0.079	[0.057,0.093]	0.349*	[0.330,0.360]	0.327*	[0.311,0.338]	0.030	[0.017,0.041]
200	20	0.059	[0.048,0.066]	0.021	[0.014,0.028]	0.099	[0.088,0.111]	0.312*	[0.304,0.326]	0.324*	[0.305,0.340]	0.028	[0.014,0.046]
	40	0.038	[0.022,0.055]	0.017	[0.010,0.026]	0.091	[0.080,0.106]	0.301*	[0.288,0.316]	0.315*	[0.293,0.324]	0.039	[0.018,0.059]
	70	0.045	[0.034,0.054]	0.014	[0.008,0.027]	0.105	[0.094,0.114]	0.304*	[0.290,0.318]	0.312*	[0.294,0.332]	0.049	[0.040,0.064]
N	C (%)	RF		RSF		CoxBoost		AftTree		WeiTree		CphTree	
		$R^2$	$R^2(25\%,75\%)$	$R^2$	$R^2(25\%,75\%)$	$R^2$	$R^2(25\%,75\%)$	$R^2$	$R^2(25\%,75\%)$	$R^2$	$R^2(25\%,75\%)$	$R^2$	$R^2(25\%,75\%)$
30	20	0.282	[0.268,0.298]	0.249	[0.236,0.262]	0.323*	[0.315,0.332]	0.226	[0.211,0.240]	0.252	[0.236,0.260]	0.226	[0.219,0.242]
	40	0.277	[0.263,0.285]	0.237	[0.224,0.248]	0.324*	[0.314,0.336]	0.253	[0.246,0.265]	0.258	[0.251,0.267]	0.264	[0.252,0.271]
	70	0.274	[0.267,0.288]	0.238	[0.223,0.251]	0.306*	[0.292,0.316]	0.269	[0.247,0.284]	0.239	[0.229,0.251]	0.254	[0.242,0.273]
70	20	0.300	[0.282,0.315]	0.227	[0.214,0.239]	0.304*	[0.293,0.318]	0.255	[0.247,0.276]	0.259	[0.244,0.271]	0.247	[0.234,0.257]
	40	0.279	[0.267,0.299]	0.238	[0.227,0.244]	0.315*	[0.302,0.335]	0.261	[0.253,0.271]	0.261	[0.249,0.274]	0.272	[0.262,0.281]
	70	0.283	[0.270,0.300]	0.233	[0.218,0.241]	0.312*	[0.301,0.335]	0.276	[0.262,0.284]	0.252	[0.242,0.269]	0.280	[0.264,0.283]
100	20	0.277	[0.267,0.286]	0.211	[0.199,0.231]	0.312*	[0.293,0.321]	0.267	[0.259,0.279]	0.234	[0.220,0.241]	0.268	[0.249,0.263]
	40	0.269	[0.256,0.280]	0.252	[0.218,0.290]	0.327*	[0.322,0.340]	0.274	[0.258,0.286]	0.258	[0.247,0.271]	0.239	[0.225,0.254]
	70	0.282	[0.269,0.299]	0.231	[0.224,0.244]	0.322*	[0.309,0.337]	0.271	[0.260,0.296]	0.234	[0.218,0.256]	0.238	[0.219,0.259]
200	20	0.274	[0.264,0.297]	0.226	[0.216,0.235]	0.340*	[0.328,0.352]	0.255	[0.239,0.274]	0.264	[0.247,0.271]	0.260	[0.248,0.278]
	40	0.301	[0.290,0.310]	0.214	[0.199,0.235]	0.322*	[0.313,0.339]	0.270	[0.253,0.277]	0.265	[0.251,0.271]	0.264	[0.236,0.293]
	70	0.291	[0.279,0.309]	0.230	[0.213,0.235]	0.310*	[0.297,0.325]	0.297	[0.259,0.317]	0.255	[0.248,0.261]	0.282	[0.253,0.303]

Table 12: Concordance index (CI) and inter-quartile region for data generated by the AFT model. Top 3 methods in each row are marked with an asterisk.

N	C (%)	AftLinear		WeiLinear		CphLinear		CphL1		CphL2		Bagging	
		CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)
30	20	0.587	[0.582,0.597]	0.610	[0.594,0.624]	0.539	[0.530,0.548]	0.663*	[0.651,0.673]	0.551	[0.538,0.568]	0.755*	[0.746,0.765]
	40	0.612	[0.597,0.624]	0.586	[0.576,0.596]	0.552	[0.544,0.559]	0.667*	[0.659,0.681]	0.579	[0.556,0.591]	0.637	[0.625,0.645]
	70	0.600	[0.587,0.614]	0.595	[0.582,0.604]	0.557	[0.546,0.568]	0.642*	[0.631,0.653]	0.552	[0.525,0.567]	0.613	[0.597,0.626]
70	20	0.606	[0.592,0.617]	0.606	[0.593,0.617]	0.558	[0.549,0.576]	0.652*	[0.637,0.670]	0.574	[0.564,0.590]	0.632*	[0.616,0.656]
	40	0.603	[0.593,0.615]	0.599	[0.584,0.610]	0.565	[0.555,0.578]	0.660*	[0.656,0.676]	0.562	[0.553,0.575]	0.645*	[0.631,0.656]
	70	0.612	[0.599,0.623]	0.599	[0.586,0.609]	0.515	[0.507,0.539]	0.675*	[0.662,0.688]	0.556	[0.540,0.566]	0.646*	[0.631,0.661]
100	20	0.572	[0.551,0.600]	0.612	[0.595,0.624]	0.540	[0.525,0.552]	0.669*	[0.658,0.687]	0.567	[0.554,0.578]	0.632*	[0.620,0.647]
	40	0.579	[0.565,0.596]	0.602	[0.590,0.610]	0.554	[0.541,0.566]	0.647*	[0.639,0.662]	0.566	[0.555,0.575]	0.617	[0.599,0.641]
	70	0.597	[0.571,0.613]	0.623	[0.606,0.634]	0.532	[0.517,0.542]	0.650*	[0.633,0.674]	0.568	[0.559,0.577]	0.641*	[0.628,0.663]
200	20	0.590	[0.585,0.600]	0.617	[0.604,0.628]	0.523	[0.509,0.553]	0.658*	[0.645,0.669]	0.552	[0.540,0.562]	0.640*	[0.630,0.651]
	40	0.601	[0.588,0.612]	0.618*	[0.602,0.634]	0.531	[0.522,0.543]	0.650*	[0.628,0.679]	0.568	[0.559,0.578]	0.658*	[0.647,0.670]
	70	0.598	[0.587,0.608]	0.586	[0.574,0.597]	0.555	[0.543,0.564]	0.650*	[0.631,0.659]	0.585	[0.551,0.616]	0.660*	[0.644,0.675]
N	C (%)	RF		RSF		CoxBoost		AftTree		WeiTree		CphTree	
		CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)	CI	CI(25%,75%)
30	20	0.730*	[0.722,0.738]	0.584	[0.570,0.598]	0.603	[0.588,0.612]	0.605	[0.597,0.615]	0.590	[0.576,0.599]	0.597	[0.586,0.609]
	40	0.635*	[0.622,0.641]	0.584	[0.572,0.598]	0.599	[0.587,0.608]	0.620	[0.612,0.632]	0.606	[0.597,0.613]	0.595	[0.586,0.605]
	70	0.630*	[0.620,0.639]	0.583	[0.559,0.592]	0.593	[0.583,0.602]	0.626*	[0.608,0.638]	0.608	[0.597,0.618]	0.606	[0.595,0.615]
70	20	0.619	[0.602,0.632]	0.591	[0.574,0.604]	0.588	[0.572,0.604]	0.596	[0.586,0.608]	0.583	[0.568,0.597]	0.620*	[0.607,0.630]
	40	0.627*	[0.620,0.639]	0.605	[0.589,0.618]	0.602	[0.585,0.614]	0.598	[0.587,0.612]	0.606	[0.594,0.612]	0.596	[0.588,0.607]
	70	0.621	[0.609,0.631]	0.590	[0.579,0.603]	0.603	[0.591,0.613]	0.585	[0.572,0.606]	0.573	[0.558,0.592]	0.622*	[0.602,0.641]
100	20	0.647*	[0.635,0.657]	0.600	[0.572,0.618]	0.583	[0.573,0.602]	0.615	[0.603,0.621]	0.622	[0.601,0.637]	0.601	[0.592,0.615]
	40	0.625*	[0.616,0.631]	0.574	[0.558,0.586]	0.599	[0.585,0.611]	0.605	[0.594,0.614]	0.620*	[0.593,0.637]	0.577	[0.567,0.591]
	70	0.626*	[0.618,0.637]	0.582	[0.573,0.596]	0.603	[0.596,0.610]	0.592	[0.581,0.603]	0.587	[0.574,0.604]	0.583	[0.577,0.592]
200	20	0.636*	[0.623,0.643]	0.563	[0.549,0.579]	0.602	[0.592,0.614]	0.597	[0.584,0.607]	0.585	[0.573,0.602]	0.618	[0.600,0.633]
	40	0.605	[0.586,0.631]	0.554	[0.547,0.567]	0.609	[0.592,0.623]	0.582	[0.573,0.597]	0.605	[0.594,0.615]	0.600	[0.586,0.611]
	70	0.631*	[0.612,0.643]	0.555	[0.536,0.585]	0.570	[0.561,0.588]	0.606	[0.593,0.613]	0.584	[0.561,0.600]	0.597	[0.589,0.608]

Table 13: TP rate and 95%CI for data generated by the CPH model. Top 3 methods in each row are marked with an asterisk.

N	C (%)	AftLinear			WeiLinear			CphLinear			CphL1			CphL2			Bagging		
		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI	
30	20	0.269	[0.246,0.292]	0.277	[0.255,0.299]	0.270	[0.249,0.291]	0.357	[0.329,0.385]	0.431*	[0.410,0.452]	0.370	[0.346,0.394]						
	40	0.270	[0.246,0.294]	0.273	[0.250,0.296]	0.282	[0.262,0.302]	0.348	[0.327,0.369]	0.441*	[0.421,0.461]	0.347	[0.323,0.371]						
	70	0.287	[0.268,0.306]	0.302	[0.283,0.321]	0.290	[0.268,0.312]	0.345	[0.322,0.368]	0.447*	[0.424,0.470]	0.388	[0.362,0.414]						
70	20	0.293	[0.273,0.313]	0.265	[0.243,0.287]	0.314	[0.293,0.335]	0.375	[0.351,0.399]	0.435*	[0.414,0.456]	0.374	[0.351,0.397]						
	40	0.277	[0.256,0.298]	0.288	[0.263,0.313]	0.273	[0.250,0.296]	0.361	[0.339,0.383]	0.445*	[0.423,0.467]	0.374	[0.353,0.395]						
	70	0.288	[0.266,0.310]	0.275	[0.252,0.298]	0.297	[0.273,0.321]	0.346	[0.321,0.371]	0.452*	[0.431,0.473]	0.368	[0.348,0.388]						
100	20	0.264	[0.242,0.286]	0.292	[0.267,0.317]	0.271	[0.246,0.296]	0.350	[0.331,0.369]	0.446*	[0.420,0.472]	0.368	[0.345,0.391]						
	40	0.277	[0.255,0.299]	0.306	[0.282,0.330]	0.288	[0.264,0.312]	0.362	[0.340,0.384]	0.433*	[0.411,0.455]	0.357	[0.334,0.380]						
	70	0.261	[0.240,0.282]	0.266	[0.245,0.287]	0.277	[0.250,0.304]	0.367	[0.341,0.393]	0.434*	[0.406,0.462]	0.368	[0.347,0.389]						
200	20	0.293	[0.273,0.313]	0.301	[0.282,0.320]	0.282	[0.261,0.303]	0.367	[0.344,0.390]	0.430*	[0.407,0.453]	0.379	[0.357,0.401]						
	40	0.278	[0.257,0.299]	0.284	[0.262,0.306]	0.290	[0.268,0.312]	0.356	[0.334,0.378]	0.414*	[0.388,0.440]	0.350	[0.325,0.375]						
	70	0.278	[0.256,0.300]	0.276	[0.255,0.297]	0.310	[0.286,0.334]	0.366	[0.345,0.387]	0.438*	[0.416,0.460]	0.362	[0.339,0.385]						
N	C (%)	RF			RSF			CoxBoost			AftTree			WeiTree			CphTree		
		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI	
30	20	0.365	[0.344,0.386]	0.336	[0.313,0.359]	0.490*	[0.467,0.513]	0.357	[0.334,0.380]	0.410*	[0.391,0.429]	0.380	[0.358,0.402]						
	40	0.351	[0.329,0.373]	0.310	[0.286,0.334]	0.496*	[0.480,0.512]	0.371	[0.348,0.394]	0.413*	[0.390,0.436]	0.374	[0.350,0.398]						
	70	0.342	[0.321,0.363]	0.306	[0.287,0.325]	0.480*	[0.456,0.504]	0.373	[0.354,0.392]	0.427*	[0.406,0.448]	0.395	[0.372,0.418]						
70	20	0.356	[0.335,0.377]	0.302	[0.282,0.322]	0.494*	[0.472,0.516]	0.366	[0.344,0.388]	0.438*	[0.413,0.463]	0.409	[0.387,0.431]						
	40	0.376	[0.353,0.399]	0.315	[0.296,0.334]	0.476*	[0.452,0.500]	0.350	[0.330,0.370]	0.438*	[0.417,0.459]	0.410	[0.386,0.434]						
	70	0.364	[0.341,0.387]	0.336	[0.314,0.358]	0.486*	[0.467,0.505]	0.368	[0.342,0.394]	0.438*	[0.415,0.461]	0.403	[0.377,0.429]						
100	20	0.382	[0.360,0.404]	0.321	[0.303,0.339]	0.496*	[0.474,0.518]	0.373	[0.349,0.397]	0.421*	[0.400,0.442]	0.398	[0.375,0.421]						
	40	0.381	[0.364,0.398]	0.305	[0.280,0.330]	0.472*	[0.455,0.489]	0.362	[0.340,0.384]	0.423*	[0.403,0.443]	0.416	[0.389,0.443]						
	70	0.346	[0.325,0.367]	0.312	[0.290,0.334]	0.496*	[0.471,0.521]	0.369	[0.343,0.395]	0.420*	[0.396,0.444]	0.394	[0.373,0.415]						
200	20	0.369	[0.345,0.393]	0.321	[0.299,0.343]	0.478*	[0.454,0.502]	0.375	[0.353,0.397]	0.448*	[0.422,0.474]	0.390	[0.367,0.413]						
	40	0.361	[0.338,0.384]	0.314	[0.292,0.336]	0.472*	[0.455,0.489]	0.388	[0.367,0.409]	0.428*	[0.404,0.452]	0.394	[0.368,0.420]						
	70	0.358	[0.340,0.376]	0.323	[0.300,0.346]	0.477*	[0.456,0.498]	0.377	[0.353,0.401]	0.434*	[0.416,0.452]	0.411	[0.385,0.437]						

Table 14: TP rate and 95%CI for data generated by the WEI model. Top 3 methods in each row are marked with an asterisk.

N	C (%)	AftLinear			WeiLinear			CphLinear			CphL1			CphL2			Bagging		
		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI	
30	20	0.277	[0.256,0.298]	0.295	[0.275,0.315]	0.291	[0.270,0.312]	0.355	[0.329,0.381]	0.427*	[0.400,0.454]	0.355	[0.331,0.379]						
	40	0.268	[0.247,0.289]	0.310	[0.288,0.332]	0.284	[0.261,0.307]	0.362	[0.340,0.384]	0.450*	[0.425,0.475]	0.374	[0.348,0.400]						
	70	0.277	[0.255,0.299]	0.270	[0.249,0.291]	0.277	[0.257,0.297]	0.358	[0.335,0.381]	0.450*	[0.428,0.472]	0.366	[0.344,0.388]						
70	20	0.283	[0.260,0.306]	0.293	[0.276,0.310]	0.293	[0.272,0.314]	0.358	[0.336,0.380]	0.445*	[0.423,0.467]	0.338	[0.315,0.361]						
	40	0.272	[0.255,0.289]	0.303	[0.281,0.325]	0.278	[0.254,0.302]	0.363	[0.338,0.388]	0.431*	[0.408,0.454]	0.339	[0.314,0.364]						
	70	0.283	[0.258,0.308]	0.294	[0.272,0.316]	0.294	[0.274,0.314]	0.366	[0.345,0.387]	0.445*	[0.422,0.468]	0.390	[0.366,0.414]						
100	20	0.291	[0.273,0.309]	0.298	[0.270,0.326]	0.281	[0.262,0.300]	0.366	[0.343,0.389]	0.414*	[0.392,0.436]	0.374	[0.348,0.400]						
	40	0.266	[0.245,0.287]	0.292	[0.271,0.313]	0.278	[0.257,0.299]	0.373	[0.349,0.397]	0.439*	[0.417,0.461]	0.355	[0.333,0.377]						
	70	0.276	[0.254,0.298]	0.297	[0.275,0.319]	0.275	[0.254,0.296]	0.357	[0.335,0.379]	0.446*	[0.428,0.464]	0.362	[0.341,0.383]						
200	20	0.281	[0.259,0.303]	0.267	[0.248,0.286]	0.314	[0.291,0.337]	0.346	[0.317,0.375]	0.446*	[0.425,0.467]	0.371	[0.349,0.393]						
	40	0.281	[0.262,0.300]	0.292	[0.271,0.313]	0.292	[0.270,0.314]	0.356	[0.338,0.374]	0.443*	[0.419,0.467]	0.362	[0.340,0.384]						
	70	0.274	[0.251,0.297]	0.298	[0.276,0.320]	0.272	[0.252,0.292]	0.372	[0.348,0.396]	0.472*	[0.450,0.494]	0.373	[0.350,0.396]						
N	C (%)	RF			CoxBoost			AftTree			WeiTree			CphTree					
		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI				
30	20	0.348	[0.329,0.367]	0.299	[0.274,0.324]	0.484*	[0.462,0.506]	0.360	[0.338,0.382]	0.407	[0.385,0.429]	0.418*	[0.399,0.437]						
	40	0.341	[0.320,0.362]	0.328	[0.305,0.351]	0.474*	[0.453,0.495]	0.367	[0.350,0.384]	0.428*	[0.406,0.450]	0.413	[0.390,0.436]						
	70	0.367	[0.345,0.389]	0.310	[0.284,0.336]	0.487*	[0.466,0.508]	0.374	[0.356,0.392]	0.419*	[0.401,0.437]	0.392	[0.370,0.414]						
70	20	0.360	[0.337,0.383]	0.340	[0.320,0.360]	0.469*	[0.446,0.492]	0.394	[0.372,0.416]	0.398*	[0.376,0.420]	0.373	[0.351,0.395]						
	40	0.358	[0.333,0.383]	0.318	[0.297,0.339]	0.492*	[0.473,0.511]	0.354	[0.335,0.373]	0.448*	[0.425,0.471]	0.393	[0.370,0.416]						
	70	0.371	[0.348,0.394]	0.323	[0.304,0.342]	0.495*	[0.470,0.520]	0.366	[0.342,0.390]	0.431*	[0.409,0.453]	0.391	[0.366,0.416]						
100	20	0.375	[0.351,0.399]	0.326	[0.303,0.349]	0.490*	[0.468,0.512]	0.373	[0.349,0.397]	0.425*	[0.402,0.446]	0.424	[0.402,0.446]						
	40	0.377	[0.353,0.401]	0.318	[0.299,0.337]	0.492*	[0.468,0.516]	0.370	[0.352,0.388]	0.412*	[0.388,0.436]	0.404	[0.383,0.425]						
	70	0.360	[0.338,0.382]	0.314	[0.292,0.336]	0.483*	[0.462,0.504]	0.402	[0.377,0.427]	0.446*	[0.418,0.474]	0.396	[0.373,0.419]						
200	20	0.339	[0.319,0.359]	0.333	[0.313,0.353]	0.498*	[0.476,0.520]	0.370	[0.349,0.391]	0.414*	[0.390,0.438]	0.407	[0.385,0.429]						
	40	0.370	[0.351,0.389]	0.322	[0.300,0.344]	0.487*	[0.464,0.510]	0.368	[0.342,0.394]	0.436*	[0.416,0.456]	0.418	[0.398,0.438]						
	70	0.355	[0.331,0.379]	0.306	[0.281,0.331]	0.458*	[0.432,0.484]	0.368	[0.345,0.391]	0.410*	[0.385,0.435]	0.393	[0.372,0.414]						

Table 15: TP rate and 95%CI for data generated by the AFT model. Top 3 methods in each row are marked with an asterisk.

N	C (%)	AftLinear			WeiLinear			CphLinear			CphL1			CphL2			Bagging		
		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI	
30	20	0.284	[0.267,0.301]	0.275	[0.250,0.300]	0.263	[0.246,0.280]	0.367	[0.345,0.389]	0.427*	[0.408,0.446]	0.379	[0.356,0.402]						
	40	0.283	[0.261,0.305]	0.277	[0.256,0.298]	0.279	[0.253,0.305]	0.345	[0.323,0.367]	0.440*	[0.417,0.463]	0.368	[0.346,0.390]						
	70	0.283	[0.259,0.307]	0.288	[0.262,0.314]	0.302	[0.281,0.323]	0.367	[0.345,0.389]	0.442*	[0.418,0.466]	0.351	[0.327,0.375]						
70	20	0.282	[0.261,0.303]	0.284	[0.260,0.308]	0.294	[0.274,0.314]	0.376	[0.351,0.401]	0.438*	[0.413,0.463]	0.362	[0.341,0.383]						
	40	0.285	[0.264,0.306]	0.294	[0.272,0.316]	0.288	[0.264,0.312]	0.389	[0.365,0.413]	0.462*	[0.438,0.486]	0.366	[0.340,0.392]						
	70	0.254	[0.232,0.276]	0.297	[0.273,0.321]	0.304	[0.282,0.326]	0.359	[0.339,0.379]	0.445*	[0.423,0.467]	0.351	[0.328,0.374]						
100	20	0.276	[0.251,0.301]	0.284	[0.262,0.306]	0.292	[0.269,0.315]	0.353	[0.335,0.371]	0.454*	[0.430,0.478]	0.352	[0.329,0.375]						
	40	0.275	[0.250,0.300]	0.302	[0.280,0.324]	0.272	[0.247,0.297]	0.384	[0.363,0.405]	0.442*	[0.422,0.462]	0.361	[0.337,0.385]						
	70	0.295	[0.275,0.315]	0.281	[0.259,0.303]	0.291	[0.266,0.316]	0.370	[0.348,0.392]	0.451*	[0.428,0.474]	0.353	[0.332,0.374]						
200	20	0.274	[0.250,0.298]	0.296	[0.273,0.319]	0.274	[0.254,0.294]	0.346	[0.323,0.369]	0.455*	[0.433,0.477]	0.356	[0.331,0.381]						
	40	0.288	[0.264,0.312]	0.300	[0.281,0.319]	0.292	[0.273,0.311]	0.373	[0.347,0.399]	0.449*	[0.424,0.474]	0.340	[0.318,0.362]						
	70	0.256	[0.234,0.278]	0.284	[0.259,0.309]	0.306	[0.281,0.331]	0.343	[0.322,0.364]	0.462*	[0.441,0.483]	0.353	[0.331,0.375]						
N	C (%)	RF			RSF			CoxBoost			AftTree			WeiTree			CphTree		
		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI		TP	95%CI	
30	20	0.368	[0.349,0.387]	0.310	[0.293,0.327]	0.465*	[0.443,0.487]	0.361	[0.336,0.386]	0.424*	[0.401,0.447]	0.390	[0.367,0.413]						
	40	0.370	[0.350,0.390]	0.343	[0.318,0.368]	0.501*	[0.475,0.527]	0.360	[0.340,0.380]	0.430*	[0.406,0.454]	0.418	[0.394,0.442]						
	70	0.379	[0.360,0.398]	0.298	[0.276,0.320]	0.474*	[0.450,0.498]	0.369	[0.349,0.389]	0.426*	[0.402,0.450]	0.406	[0.387,0.425]						
70	20	0.340	[0.315,0.365]	0.302	[0.279,0.325]	0.459*	[0.434,0.484]	0.387	[0.365,0.409]	0.423*	[0.404,0.442]	0.401	[0.378,0.424]						
	40	0.376	[0.353,0.399]	0.319	[0.299,0.339]	0.479*	[0.458,0.500]	0.338	[0.311,0.365]	0.438*	[0.414,0.462]	0.400	[0.379,0.421]						
	70	0.389	[0.368,0.410]	0.320	[0.297,0.343]	0.483*	[0.462,0.504]	0.367	[0.343,0.391]	0.430*	[0.405,0.455]	0.415	[0.390,0.440]						
100	20	0.345	[0.323,0.367]	0.323	[0.303,0.343]	0.489*	[0.469,0.509]	0.372	[0.351,0.393]	0.438*	[0.415,0.461]	0.395	[0.368,0.422]						
	40	0.342	[0.322,0.362]	0.314	[0.296,0.332]	0.488*	[0.465,0.511]	0.360	[0.342,0.378]	0.423*	[0.399,0.447]	0.413	[0.393,0.433]						
	70	0.362	[0.342,0.382]	0.309	[0.289,0.329]	0.487*	[0.465,0.509]	0.371	[0.348,0.394]	0.414*	[0.392,0.436]	0.410	[0.388,0.432]						
200	20	0.355	[0.332,0.378]	0.315	[0.290,0.340]	0.482*	[0.460,0.504]	0.372	[0.350,0.394]	0.439*	[0.415,0.463]	0.406	[0.383,0.429]						
	40	0.347	[0.328,0.366]	0.323	[0.299,0.347]	0.520*	[0.500,0.540]	0.371	[0.347,0.395]	0.445*	[0.425,0.465]	0.402	[0.378,0.426]						
	70	0.351	[0.330,0.372]	0.322	[0.302,0.342]	0.474*	[0.451,0.497]	0.372	[0.348,0.396]	0.410	[0.389,0.431]	0.411*	[0.386,0.436]						

## 4 Computation Details

### 4.1 Size of Trees

The number of regression trees  $M$  set for the tree-ensemble methods dictates how often a covariate will be selected to be part of the model. As Chipman *et al.* (2010) showed that setting a relatively small number of trees benefits the variable selection procedure since variables compete with each other to improve fit and therefore, relevant predictors should appear more frequently in the tree model. Because we were interested in exploring the BART variable selection feature, we set the number of trees  $M = 40$ , which also reduces computation time without losing predictive performance. We varied the number of trees from 20 to 120 and found that our results are relatively stable to the specification of this parameter (See Figure 1).

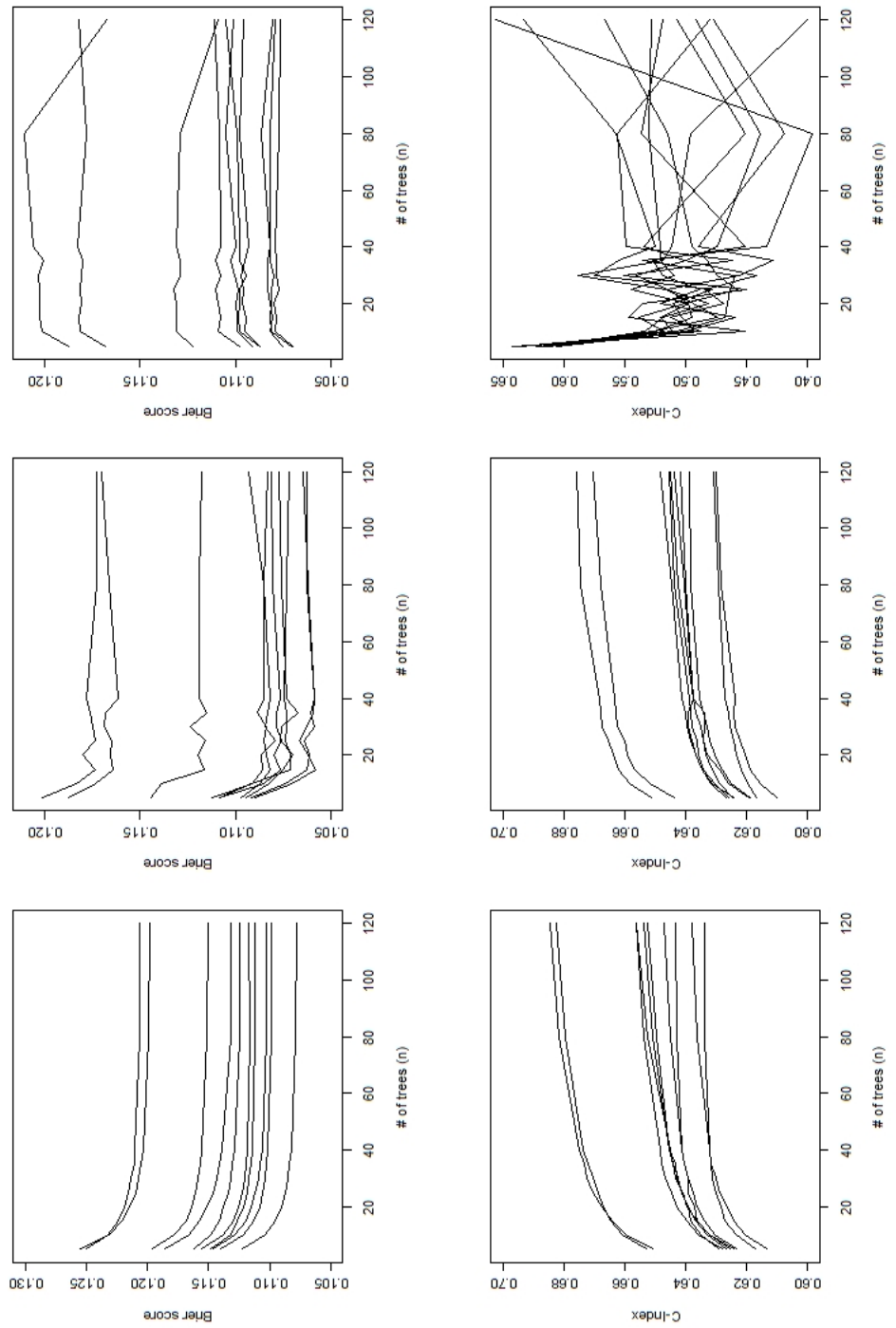


Figure 1: **Size of trees.** Figure shows the BS for the test data depending on the number of trees set for the BART model. Left plot - AFT-TREE; center - WEI-TREE; Right - CPH-TREE. Each line represents one training/test split of data.

## 4.2 Computation time

The computational effort required to evaluate models of large-scale datasets, such as those involving genomic data, is quite modest, due to the latent variable construction of our models, which allows the use of efficient MCMC simulation algorithms. The algorithmic complexity of the drawing scheme for the CPH model described in section 2.4 of the manuscript, for example, will be the number of iterations,  $K$ , times the complexity of each step. Chipman *et al.* (2010) established experimentally that updating the tree parameters, step 1, is  $O(n)$ . Step 3 updates  $n w_i$  from the density summaries and so is also  $O(n)$ . Other computations within each iteration, such as updating all survival model parameters by drawing from full conditional distributions, do not depend on the problem size and are thus  $O(1)$ . The overall complexity is thus  $O(Kn)$ . The total number of iterations required is an open problem, but in practice we choose a large number, such as 10000, and verify convergence. For a fixed  $K$ , therefore, the computational time required is linear in the number of samples,  $n$ .

In this section, we report the simulation times of our methods for various samples sizes and show that our methods scale reasonably to large datasets (Table 16). The analysis were run in a PC Intel® Core<sup>(TM)</sup>2 Quad CPU Q9300 with processor speed of 2.50Ghz and 8.00GB of memory. The time modes were obtained from the simulation study and, therefore, the same data set structure was used, i.e., various  $N$  and percentages of censoring with number of covariates  $p = 200$  and number of chains  $k = 10000$ .

Table 16: Mode of time (seconds) for calculations in the Bayesian tree-ensemble models as function of the sample size with  $p = 200$ .

N	CPH-TREE	WEI-TREE	AFT-TREE
30	220	183	217
70	241	223	227
100	252	249	253
200	312	298	304

## 4.3 Convergence

In this section we provide plots (Figure 2) which depict the convergence properties of our proposed models. Three plots are provided to show the chains for one example of latent variable per model and, for all of them, the convergence is very quick.



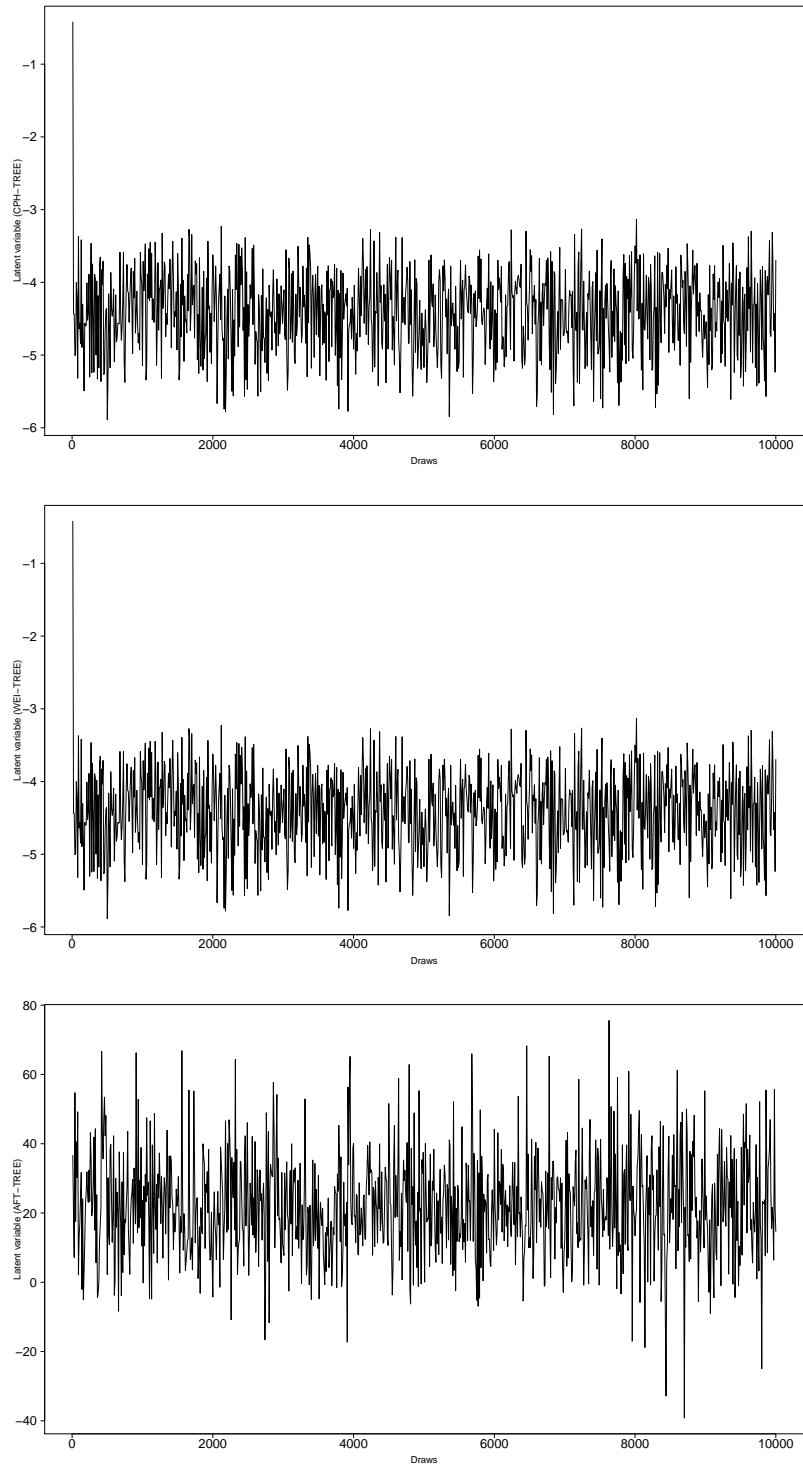


Figure 2: **Convergence.** Figure shows the chains for the latent variables. Only each tenth was plotted.

## 5 High-resolution Figures

In this section, we show main text plots in higher resolutions.

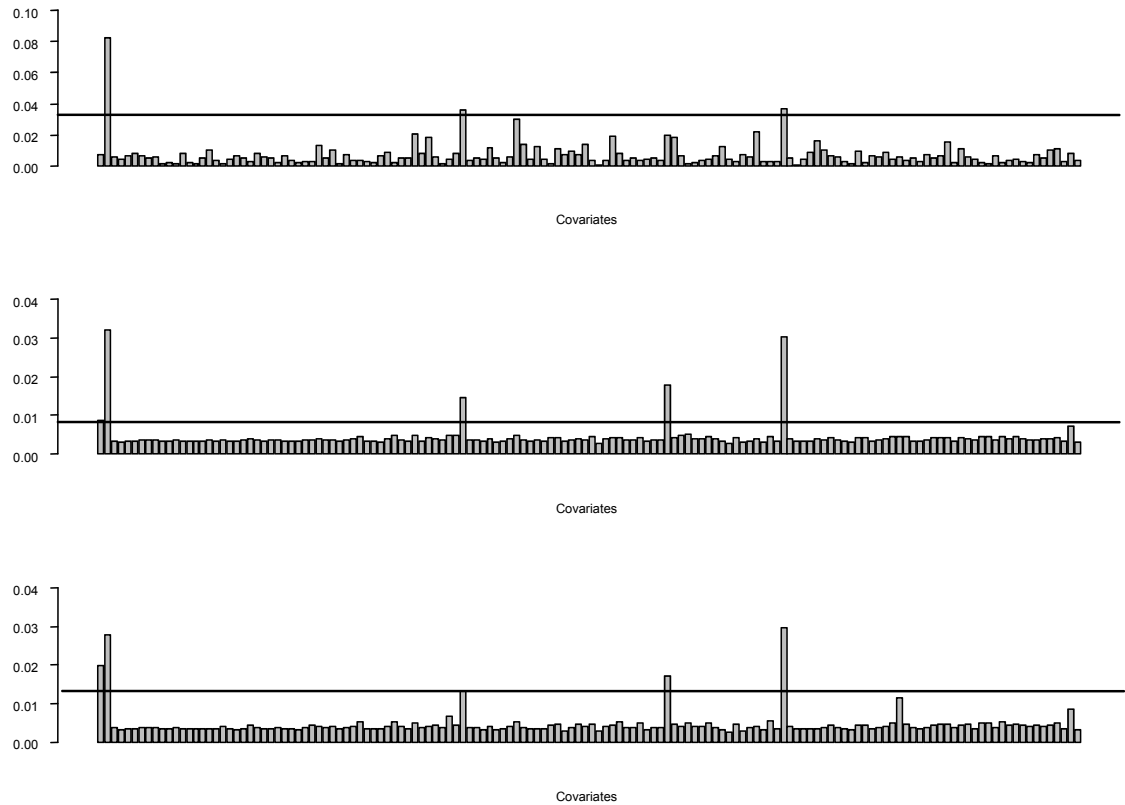


Figure 3: Posterior probability of a variable appearing in the CPH-TREE (top), WEI-TREE (center), and AFT-TREE (bottom) survival ensemble methods as applied to the brain tumor data. Variables with posterior probability above the horizontal gray line are considered to be significantly used; controlled by 10% FDR.

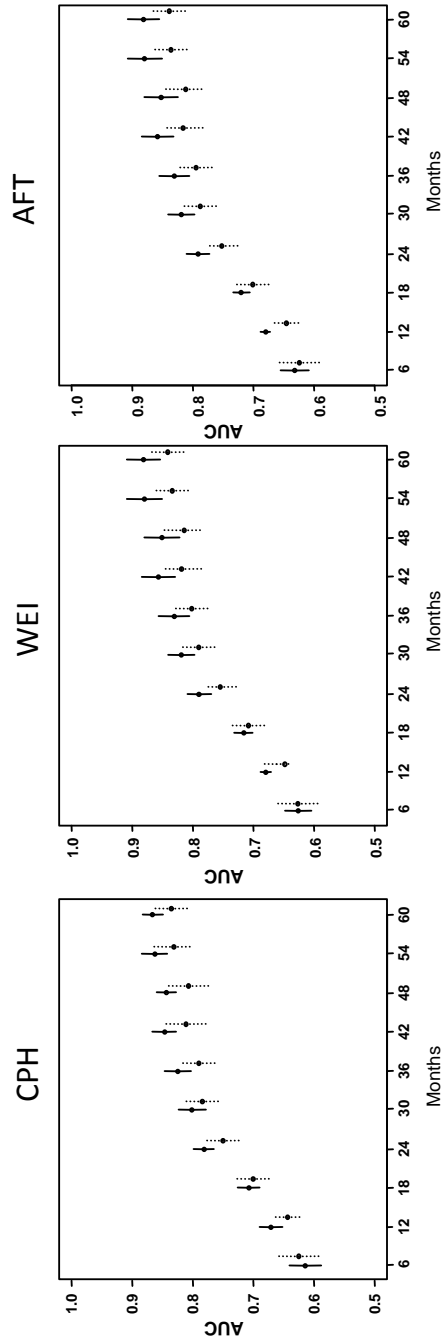


Figure 4: **Time-dependent AUC analysis.** The plots compare the performance of the proposed tree-ensemble methods with their multivariable linear versions, as applied to the brain tumor data. Dots represent the medians across splits of training/test sets; lines depict the interquartile limits. Left plot: CPH (dashed lines) and CPH-TREE (solid lines); Center plot: Weibull (dashed) and WEI-TREE (solid); Right plot: AFT (dashed) and AFT-TREE (solid).

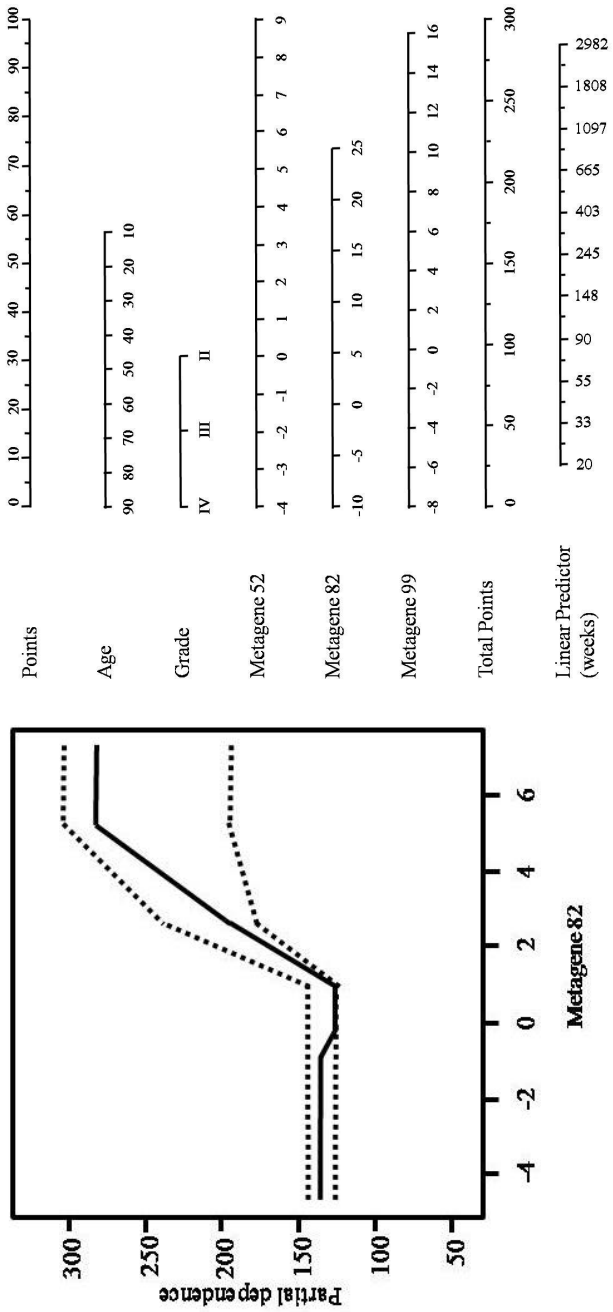


Figure 5: **Marginal effects of significant covariates.** Left panel: Partial dependence function plots for metagene 82. Y-axis scale is in weeks. Right panel: Nomogram of the most important variables in the AFT-TREE model.