Supplementary Materials for "It's integral: Replacing the trapezoidal rule to remove bias and correctly impute censored covariates with their conditional means"

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Web Appendix A More About the Extrapolation Methods for Breslow's Estimator

Web Appendix A.1 Derivation of the Exponential Extension

Assuming that among the baseline group (i.e., with Z = 0), X follows an exponential distribution with rate ρ , we have $S_0(t) = \exp\{-(t/\rho)\}$. To connect to Breslow's estimator, $\widehat{\rho}$ is constrained so that $\exp\{-\left(\widetilde{X}/\widehat{\rho}\right)\} = \widehat{S}_0(\widetilde{X})$. We can solve this constraint for $\widehat{\rho} = -\widetilde{X}\log\left\{\widehat{S}_0(\widetilde{X})\right\}^{-1}$ and extrapolate using $\widehat{S}_0(t) = \exp\left(\left[t\log\left\{\widehat{S}_0(\widetilde{X})\right\}\right]/\widetilde{X}\right)$ for $t > \widetilde{X}$. This is the exponential extension described in Section 2.5.1 and originally proposed by Brown et al. (1974).

Web Appendix A.2 Derivation of the Weibull Extension

Assuming that among the baseline group (i.e., with $Z = \mathbf{0}$), X follows a Weibull distribution with shape and scale parameters ν and ρ , respectively, we have $S_0(t) = \exp(-\rho t^{\nu})$. The parameters are once again constrained to ensure a clean transition from Breslow's estimator to the extension, with $\exp(-\widehat{\rho}\widetilde{X}^{\widehat{\nu}}) = \widehat{S}_0(\widetilde{X})$. Unlike the exponential extension, there is not a closed form solution as in Web Appendix A.1. Herein, we adopt a constrained maximum likelihood approach to find $\widehat{\nu}$ and $\widehat{\rho}$.

The shape and scale parameters, ν and ρ , respectively, can be estimated directly through maximum likelihood estimation. Using the probability density function and survival function of the Weibull distribution, the usual (i.e., unconstrained) log-likelihood for the shape and scale parameters can be defined as

$$l_n(\nu, \rho) = \sum_{i=1}^n \Delta_i \log \left\{ \rho \nu W_i^{\nu-1} \exp\left(-\rho W_i^{\nu}\right) \right\} + \sum_{i=1}^n (1 - \Delta_i) \log \left\{ \exp\left(-\rho W_i^{\nu}\right) \right\}$$
$$= -\rho \sum_{i=1}^n W_i^{\nu} + (\nu - 1) \sum_{i=1}^n \Delta_i \log (W_i) + n_1 \log (\rho) + n_1 \log (\nu),$$
(S.1)

where n_1 is the number of uncensored observations (i.e., $n_1 = \sum_{i=1}^n \Delta_i$).

Recall that we want this Weibull curve to "tie into" Breslow's estimator $\widehat{S}_0(t)$ at the largest uncensored value, \widetilde{X} . This constraint on the Weibull survival function can be expressed as $\exp(-\rho \widetilde{X}^{\nu}) \equiv \widehat{S}_0(\widetilde{X})$, and it further translates into the following relationship

between the shape and scale parameters:

$$\rho = -\log \left\{ \widehat{S}_0(\widetilde{X}) \right\} / (\widetilde{X}^{\nu}). \tag{S.2}$$

With Equation (S.2), we can modify Equation (S.1) to obtain the constrained log-likelihood in terms of just the shape parameter,

$$l_n(\nu) = \left[\log \left\{ \widehat{S}_0(\widetilde{X}) \right\} / (\widetilde{X}^{\nu}) \right] \sum_{i=1}^n W_i^{\nu} + (\nu - 1) \sum_{i=1}^n \Delta_i \log (W_i)$$

$$+ n_1 \log \left[\log \left\{ \widehat{S}_0(\widetilde{X}) \right\} / (\widetilde{X}^{\nu}) \right] + n_1 \log (\nu).$$
(S.3)

Estimation of the maximum likelihood estimator (MLE) $\hat{\nu}$ is done by finding the root of Equation (S.3) with a univariate Newton-type algorithm, as implemented in the nlm function in R (R Core Team, 2019). Our initial guess for the shape parameter (which must be > 0) is $\hat{\nu}^{(0)} = 1 \text{E}^{-4}$, and the algorithm is restricted to positive values for $\hat{\nu}$. Finally, $\hat{\rho}$ is obtained by plugging $\hat{\nu}$ at convergence into Equation (S.2), and with it we arrive at the parameters for the Weibull extension used to extrapolate from Breslow's step function estimator of baseline survival, $\hat{S}_0(t)$ for $t > \tilde{X}$ introduced in Section 2.5.1.

Web Appendix A.3 Finite Upper Limit for X

In the formulas used throughout this manuscript, we integrate from W_i to infinity in calculating the conditional means. This is the most general case, and it was appropriate in our simulation studies (Section 3) because X was generated from Weibull or log-normal distributions with domains from 0 to infinity. However, in some settings we have prior information about X that allows us to replace the infinite upper bound in the integral with some known constant, denoted by ω .

For example, in our PREDICT-HD example (Section 4), the censored covariate X was TIME₀ from study entry to clinical Huntington's disease diagnosis. Since this is an adult cohort, with all subjects having $AGE_0 \geq 18$ years old at study entry, we set the longest time from study entry to clinical diagnosis to be $\omega = 60$ years. We believe this is a conservative upper bound on TIME₀ that is in agreement with the recent overall life expectancy estimate of 78 years in the United States (U.S. Census Bureau, 2017). There is no established life expectancy estimate for people who are at-risk for Huntington's disease; we call 78 years

a "conservative" upper bound, since it is probably higher than the life expectancy in our population. Choosing this finite limit is an important consideration. While we want to extract as much information from the data as we can, we also want to avoid imputing too far beyond the observed values of TIME₀ or beyond reasonable values based on the context, leading to a trade-off between setting ω too low or too high.

Now, our choice of finite ω imposes an additional constraint on the Weibull extension: since $S(\omega) \approx 0$ we further constrain ν and ρ such that $\exp(-\rho\omega^{\nu}) \approx 0$. Thus, we can find the corresponding values of $\widehat{\rho}$ and $\widehat{\nu}$ using the uniroot function in R (R Core Team, 2019), since ρ can be treated as a function of ν as in Equation (S.2).

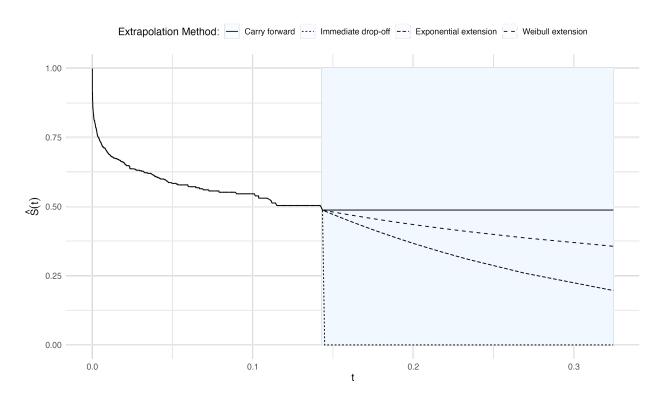


Figure S1: Illustration of the four extrapolation methods for a step survival function $\widehat{S}(t)$ in simulated data. The shaded area represents values of $t > \widetilde{X}$ (the largest uncensored value), where extrapolation is needed.

Web Appendix B Additional Results from the Simulation Studies

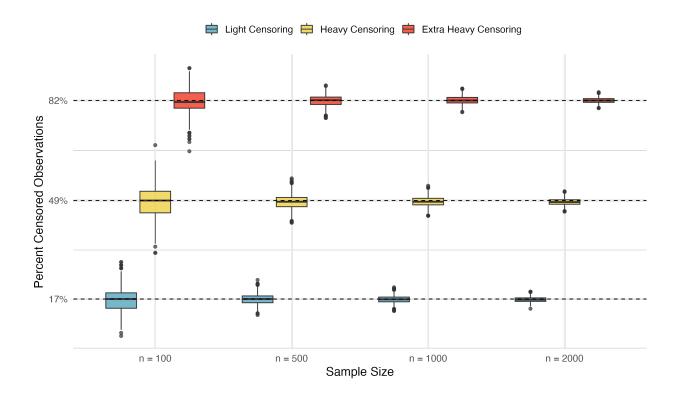


Figure S2: We explored light ($\sim 17\%$), heavy ($\sim 49\%$), and extra heavy ($\sim 82\%$) censoring in Weibull X, induced by generating C from an exponential distribution with rates = 0.5, 2.9, and 20, respectively.

Table S1: Simulation results for Weibull X from the full cohort analysis and imputation approaches using the true survival function, assuming that X was independent of Z.

		Full Cohort			Ada	ptive Qu	ıadratı	ıre	Trapezoidal Rule				
Censoring	n	Bias	(%)	SE	Bias	(%)	SE	\mathbf{RE}	Bias	(%)	SE	\mathbf{RE}	
					$\hat{\alpha}$: Inte	ercept							
Light	100	-0.003	(-0.29)	0.162	-0.003	(-0.34)	0.166	0.950	-0.007	(-0.73)	0.167	0.93	
	500	0.000	(0.02)	0.069	0.000	(0.03)	0.070	0.976	-0.001	(-0.13)	0.070	0.97	
	1000	0.000	(-0.04)	0.051	0.000	(0.01)	0.052	0.941	-0.001	(-0.11)	0.052	0.93	
	2000	0.001	(0.10)	0.035	0.001	(0.13)	0.037	0.936	0.001	(0.05)	0.037	0.93	
Heavy	100	-0.003	(-0.29)	0.162	-0.006	(-0.62)	0.183	0.783	-0.018	(-1.80)	0.189	0.73	
	500	0.000	(0.02)	0.069	0.000	(0.05)	0.078	0.798	-0.007	(-0.66)	0.079	0.76	
	1000	0.000	(-0.04)	0.051	-0.001	(-0.05)	0.056	0.811	-0.006	(-0.63)	0.057	0.78	
	2000	0.001	(0.10)	0.035	0.002	(0.16)	0.040	0.772	-0.003	(-0.28)	0.041	0.75	
Extra Heavy	100	-0.003	(-0.29)	0.162	-0.007	(-0.66)	0.241	0.450	-0.029	(-2.91)	0.269	0.36	
	500	0.000	(0.02)	0.069	-0.001	(-0.11)	0.105	0.440	-0.017	(-1.67)	0.113	0.37	
	1000	0.000	(-0.04)	0.051	0.000	(-0.03)	0.076	0.450	-0.013	(-1.35)	0.080	0.40	
	2000	0.001	(0.10)	0.035	0.002	(0.19)	0.054	0.430	-0.010	(-0.98)	0.057	0.38	
				β̂: C	oefficient o	on Censo	$\operatorname{red} X$						
Light	100	0.002	(0.40)	0.266	0.003	(0.54)	0.286	0.864	0.027	(5.40)	0.302	0.77	
	500	0.002	(0.40)	0.111	0.002	(0.36)	0.122	0.828	0.011	(2.14)	0.125	0.79	
	1000	0.001	(0.16)	0.082	-0.001	(-0.10)	0.091	0.807	0.006	(1.18)	0.092	0.78	
	2000	-0.001	(-0.18)	0.054	-0.002	(-0.42)	0.062	0.777	0.002	(0.40)	0.062	0.76	
Heavy	100	0.002	(0.40)	0.266	0.011	(2.15)	0.373	0.510	0.139	(27.72)	0.479	0.30	
	500	0.002	(0.40)	0.111	0.002	(0.48)	0.163	0.469	0.068	(13.53)	0.187	0.35	
	1000	0.001	(0.16)	0.082	0.002	(0.40)	0.117	0.485	0.053	(10.68)	0.131	0.38	
	2000	-0.001	(-0.18)	0.054	-0.002	(-0.43)	0.083	0.431	0.036	(7.11)	0.091	0.35	
Extra Heavy	100	0.002	(0.40)	0.266	0.015	(3.01)	0.678	0.154	0.881	(176.18)	1.911	0.01	
	500	0.002	(0.40)	0.111	0.007	(1.39)	0.287	0.150	0.574	(114.75)	0.640	0.03	
	1000	0.001	(0.16)	0.082	0.002	(0.48)	0.202	0.163	0.485	(96.97)	0.414	0.03	
	2000	-0.001	(-0.18)	0.054	-0.002	(-0.47)	0.146	0.139	0.414	(82.71)	0.285	0.03	
				γ̂: Co	efficient o	n Uncens	$\operatorname{sored} Z$	•					
Light	100	-0.002	(-0.84)	0.204	-0.002	(-0.61)	0.205	0.993	-0.002	(-0.63)	0.205	0.99	
	500	-0.005	(-1.98)	0.089	-0.005	(-1.99)	0.090	0.983	-0.005	(-1.98)	0.090	0.98	
	1000	-0.001	(-0.39)	0.063	-0.001	(-0.47)	0.064	0.981	-0.001	(-0.47)	0.064	0.98	
	2000	-0.002	(-0.64)	0.044	-0.002	(-0.63)	0.044	0.991	-0.002	(-0.63)	0.044	0.99	
Heavy	100	-0.002	(-0.84)	0.204	-0.001	(-0.22)	0.206	0.983	-0.001	(-0.22)	0.205	0.98	
	500	-0.005	(-1.98)	0.089	-0.005	(-1.94)	0.091	0.968	-0.005	(-1.94)	0.091	0.96	
	1000	-0.001	(-0.39)	0.063	-0.001	(-0.47)	0.065	0.961	-0.001	(-0.48)	0.065	0.96	
	2000	-0.002	(-0.64)	0.044	-0.002	(-0.70)	0.045	0.969	-0.002	(-0.70)	0.045	0.96	
Extra Heavy	100	-0.002	(-0.84)	0.204	-0.001	(-0.52)	0.207	0.973	-0.001	(-0.36)	0.206	0.97	
	500	-0.005	(-1.98)	0.089	-0.005	(-1.81)	0.091	0.962	-0.004	(-1.79)	0.091	0.96	
	1000	-0.001	(-0.39)	0.063	-0.001	(-0.56)	0.065	0.952	-0.001	(-0.58)	0.065	0.95	
	2000	-0.002	(-0.64)	0.044	-0.002	(-0.90)	0.045	0.945	-0.002	(-0.89)	0.045	0.94	

Note: Bias (%): empirical bias (empirical percent bias); SE: empirical standard error; RE: empirical relative efficiency to the full-cohort analysis. The censored covariate X was generated from a Weibull distribution with shape = 0.75 and scale = 0.25. All other variables were generated as in Section 3.1. True parameter values were $(\alpha, \beta, \gamma) = (1, 0.5, 0.25)$. All entries are based on 1000 replicates.

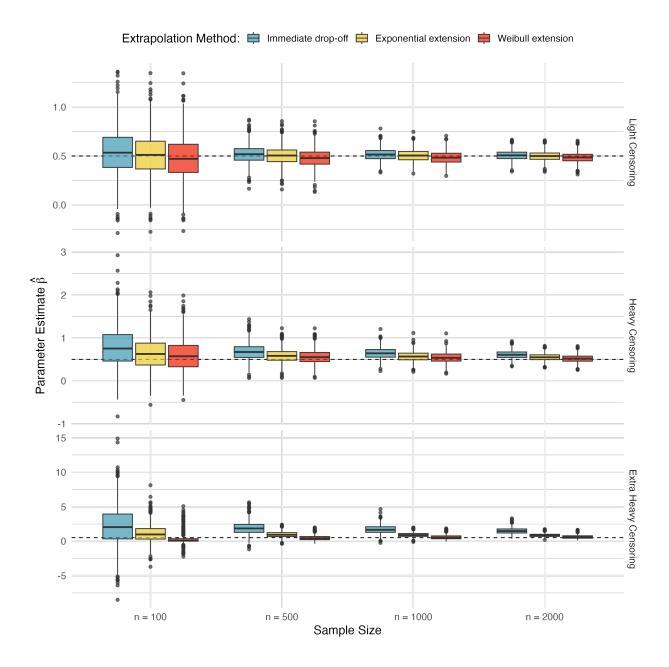


Figure S3: With Weibull X, extrapolating Breslow's estimator $\widehat{S}_0(t)$ beyond the largest uncensored value \widetilde{X} with the Weibull extension offered the lowest bias and best efficiency for $\widehat{\beta}$ in conditional mean imputation with adaptive quadrature. The dashed line denotes the true parameter value, $\beta=0.5$.

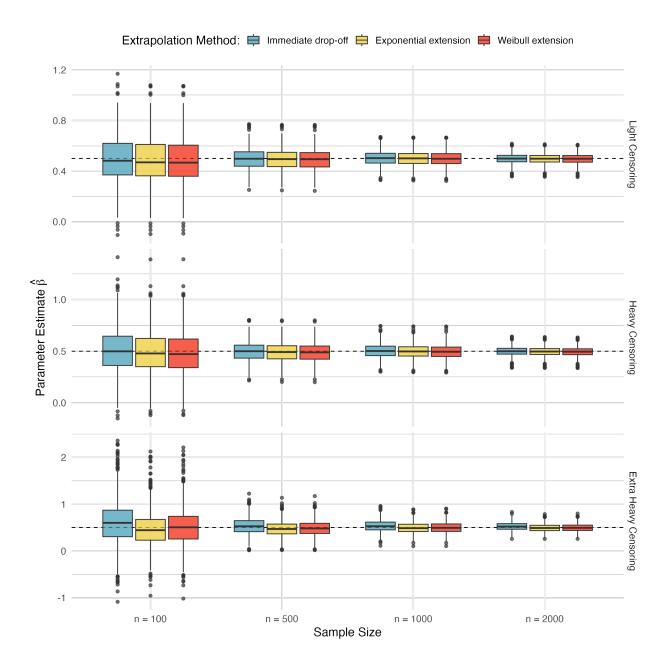


Figure S4: With log-normal X, extrapolating Breslow's estimator $\widehat{S}_0(t)$ beyond the largest uncensored value \widetilde{X} with any of the three extrapolation methods offered similar bias and efficiency for $\widehat{\beta}$ in conditional mean imputation with adaptive quadrature. The dashed line denotes the true parameter value, $\beta=0.5$.

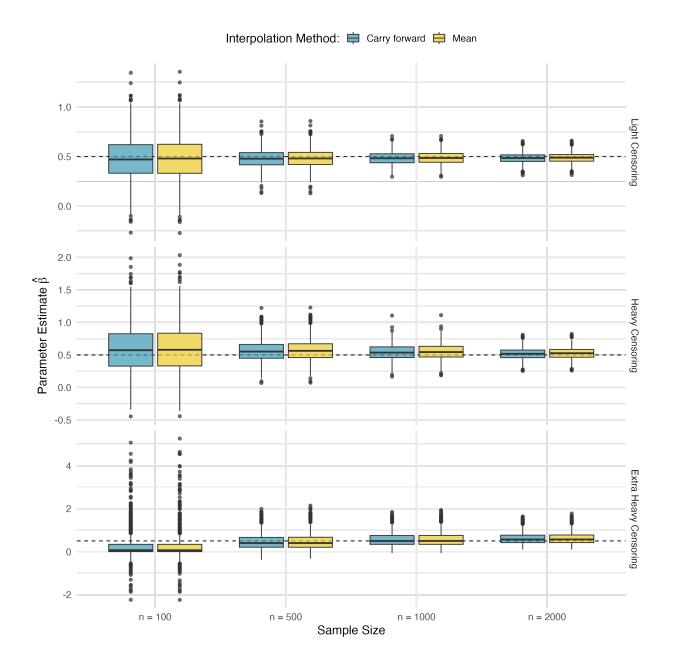


Figure S5: Interpolating Breslow's estimator $\hat{S}_0(t)$ between uncensored values with either of the two interpolation methods offered similar bias and efficiency for $\hat{\beta}$ in conditional mean imputation with adaptive quadrature. The dashed line denotes the true parameter value, $\beta=0.5$.

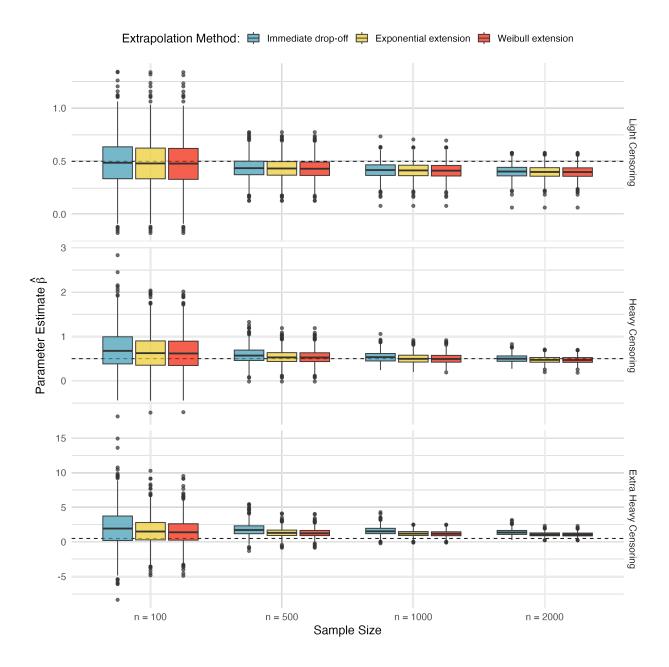


Figure S6: Extrapolating Breslow's estimator $\widehat{S}_0(t)$ beyond the largest uncensored value \widetilde{X} with any of the three extrapolation methods offered similar bias and efficiency for $\widehat{\beta}$ in conditional mean imputation with the trapezoidal rule. The dashed line denotes the true parameter value, $\beta=0.5$.

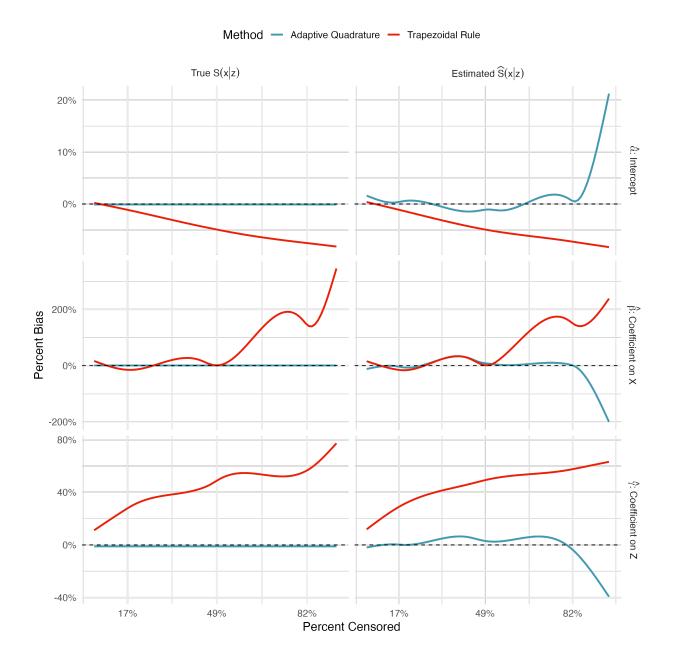


Figure S7: When using the estimated survival function $\widehat{S}(x|z)$, conditional mean imputation with adaptive quadrature could be biased under severe censoring (e.g., > 82%). This residual bias seemed to stem from the estimated survival function, since we saw virtually no bias across these same settings when using the true survival function S(x|z) instead. The solid lines denote smoothed representations of the relationship between percent censored and percent bias (per simulation, across all settings) for each method. The dashed line denotes 0% bias for reference.

Table S2: Simulation results for Weibull X from the full cohort analysis and imputation approaches using the estimated survival function, assuming that X was independent of Z.

			ıll Cohor		Ada	Adaptive Quadrature				Trapezoidal Rule			
Censoring	\boldsymbol{n}	Bias	(%)	SE	Bias	(%)	SE	RE	Bias	(%)	SE	RE	
					â: Int	ercept							
Light	100	0.002	(0.22)	0.164	0.003	(0.33)	0.168	0.948	-0.001	(-0.11)	0.169	0.936	
	500	-0.003	(-0.32)	0.068	-0.001	(-0.09)	0.070	0.945	-0.005	(-0.47)	0.071	0.939	
	1000	0.000	(0.00)	0.051	0.002	(0.20)	0.051	0.976	-0.001	(-0.10)	0.052	0.963	
	2000	0.001	(0.07)	0.037	0.002	(0.22)	0.038	0.948	0.000	(0.00)	0.038	0.946	
Heavy	100	0.002	(0.22)	0.164	-0.003	(-0.34)	0.187	0.763	-0.010	(-0.99)	0.190	0.743	
	500	-0.003	(-0.32)	0.068	-0.007	(-0.72)	0.078	0.770	-0.012	(-1.23)	0.079	0.754	
	1000	0.000	(0.00)	0.051	-0.002	(-0.22)	0.055	0.842	-0.007	(-0.69)	0.056	0.811	
	2000	0.001	(0.07)	0.037	0.000	(-0.04)	0.041	0.809	-0.005	(-0.46)	0.041	0.806	
Extra Heavy	100	0.002	(0.22)	0.164	0.020	(1.97)	0.247	0.440	-0.009	(-0.94)	0.269	0.370	
	500	-0.003	(-0.32)	0.068	-0.006	(-0.64)	0.107	0.406	-0.022	(-2.17)	0.112	0.373	
	1000	0.000	(0.00)	0.051	-0.005	(-0.48)	0.077	0.438	-0.017	(-1.69)	0.080	0.403	
	2000	0.001	(0.07)	0.037	-0.003	(-0.29)	0.056	0.427	-0.012	(-1.24)	0.058	0.404	
				β̂: C	Coefficient	on Censor	$\operatorname{red} X$						
Light	100	-0.009	(-1.85)	0.274	-0.022	(-4.39)	0.303	0.821	0.007	(1.33)	0.318	0.747	
	500	0.004	(0.74)	0.109	-0.010	(-1.91)	0.122	0.797	0.010	(2.08)	0.125	0.768	
	1000	0.005	(1.00)	0.078	-0.005	(-1.04)	0.087	0.809	0.010	(1.94)	0.088	0.791	
	2000	0.000	(-0.05)	0.056	-0.008	(-1.66)	0.063	0.783	0.002	(0.43)	0.063	0.776	
Heavy	100	-0.009	(-1.85)	0.274	0.033	(6.61)	0.448	0.376	0.114	(22.78)	0.508	0.292	
	500	0.004	(0.74)	0.109	0.031	(6.24)	0.183	0.356	0.079	(15.88)	0.192	0.322	
	1000	0.005	(1.00)	0.078	0.022	(4.34)	0.125	0.393	0.061	(12.27)	0.130	0.365	
	2000	0.000	(-0.05)	0.056	0.005	(1.03)	0.094	0.357	0.040	(8.06)	0.094	0.358	
Extra Heavy	100	-0.009	(-1.85)	0.274	-0.165	(-32.95)	0.741	0.137	0.745	(148.99)	1.905	0.021	
	500	0.004	(0.74)	0.109	0.024	(4.73)	0.398	0.075	0.600	(119.91)	0.626	0.031	
	1000	0.005	(1.00)	0.078	0.085	(16.95)	0.306	0.066	0.533	(106.57)	0.420	0.035	
	2000	0.000	(-0.05)	0.056	0.100	(19.92)	0.239	0.055	0.445	(89.00)	0.303	0.034	
				γ ̂: Co	oefficient o	n Uncens	ored Z						
Light	100	0.000	(-0.12)	0.205	0.001	(0.32)	0.206	0.991	0.000	(0.14)	0.205	1.000	
	500	0.002	(0.90)	0.090	0.002	(0.73)	0.090	0.987	0.002	(0.73)	0.090	0.991	
	1000	-0.002	(-0.88)	0.062	-0.002	(-0.91)	0.062	1.004	-0.002	(-0.84)	0.063	0.993	
	2000	-0.001	(-0.34)	0.045	-0.001	(-0.34)	0.045	0.988	-0.001	(-0.32)	0.045	0.991	
Heavy	100	0.000	(-0.12)	0.205	0.002	(0.65)	0.208	0.978	0.001	(0.24)	0.206	0.996	
	500	0.002	(0.90)	0.090	0.002	(0.70)	0.091	0.967	0.002	(0.74)	0.091	0.977	
	1000	-0.002	(-0.88)	0.062	-0.002	(-0.97)	0.063	0.974	-0.002	(-0.73)	0.064	0.956	
	2000	-0.001	(-0.34)	0.045	-0.001	(-0.30)	0.046	0.955	-0.001	(-0.28)	0.046	0.974	
Extra Heavy	100	0.000	(-0.12)	0.205	-0.005	(-1.83)	0.257	0.639	0.000	(-0.04)	0.206	0.990	
	500	0.002	(0.90)	0.090	0.004	(1.70)	0.099	0.823	0.002	(0.94)	0.091	0.970	
	1000	-0.002	(-0.88)	0.062	-0.001	(-0.39)	0.067	0.869	-0.002	(-0.63)	0.064	0.942	
	2000	-0.001	(-0.34)	0.045	0.000	(-0.20)	0.049	0.855	-0.001	(-0.25)	0.046	0.963	

Note: Bias (%): empirical bias (empirical percent bias); SE: empirical standard error; RE: empirical relative efficiency to the full-cohort analysis. The censored covariate X was generated from a Weibull distribution with shape = 0.75 and scale = 0.25. All other variables were generated as in Section 3.1. True parameter values were $(\alpha, \beta, \gamma) = (1, 0.5, 0.25)$. All entries are based on 1000 replicates.

Table S3: Simulation results for log-normal X from the full cohort analysis and imputation approaches using the estimated survival function.

		Fu	Full Cohort			ptive Qu	ıadratı	Trapezoidal Rule				
Censoring	n	Bias	(%)	SE	Bias	(%)	SE	RE	Bias	(%)	SE	RE
					â: Inte	ercept						
Light	100	-0.001	(-0.14)	0.233	0.009	(0.94)	0.251	0.862	-0.006	(-0.58)	0.252	0.850
	500	0.002	(0.17)	0.103	0.010	(1.01)	0.112	0.839	0.001	(0.13)	0.112	0.835
	1000	-0.001	(-0.10)	0.074	0.003	(0.25)	0.080	0.864	-0.005	(-0.46)	0.080	0.851
	2000	0.000	(0.02)	0.051	0.004	(0.37)	0.054	0.891	-0.003	(-0.25)	0.054	0.885
Heavy	100	-0.001	(-0.14)	0.233	0.011	(1.08)	0.270	0.744	-0.014	(-1.37)	0.277	0.706
	500	0.002	(0.17)	0.103	0.015	(1.49)	0.121	0.715	-0.001	(-0.07)	0.123	0.696
	1000	-0.001	(-0.10)	0.074	0.006	(0.62)	0.086	0.732	-0.007	(-0.68)	0.087	0.718
	2000	0.000	(0.02)	0.051	0.007	(0.67)	0.058	0.775	-0.005	(-0.47)	0.058	0.766
Extra Heavy	100	-0.001	(-0.14)	0.233	-0.017	(-1.72)	0.449	0.269	-0.072	(-7.18)	0.480	0.235
	500	0.002	(0.17)	0.103	0.017	(1.66)	0.190	0.292	-0.023	(-2.28)	0.199	0.266
	1000	-0.001	(-0.10)	0.074	0.003	(0.26)	0.138	0.287	-0.030	(-3.03)	0.143	0.267
	2000	0.000	(0.02)	0.051	0.010	(0.98)	0.094	0.289	-0.023	(-2.35)	0.097	0.276
				β̂: Co	efficient o	on Censo	$\operatorname{red} X$					
Light	100	-0.005	(-1.09)	0.165	-0.018	(-3.67)	0.185	0.795	-0.005	(-1.02)	0.187	0.777
	500	-0.001	(-0.22)	0.073	-0.009	(-1.87)	0.082	0.778	-0.004	(-0.80)	0.082	0.777
	1000	0.001	(0.23)	0.052	-0.002	(-0.39)	0.059	0.799	0.001	(0.27)	0.059	0.794
	2000	0.000	(0.07)	0.036	-0.003	(-0.53)	0.040	0.817	0.000	(-0.10)	0.040	0.816
Heavy	100	-0.005	(-1.09)	0.165	-0.021	(-4.11)	0.206	0.642	0.002	(0.36)	0.213	0.602
	500	-0.001	(-0.22)	0.073	-0.014	(-2.84)	0.091	0.631	-0.004	(-0.87)	0.092	0.629
	1000	0.001	(0.23)	0.052	-0.006	(-1.16)	0.065	0.642	0.001	(0.22)	0.066	0.637
	2000	0.000	(0.07)	0.036	-0.005	(-1.04)	0.044	0.658	-0.001	(-0.17)	0.044	0.652
Extra Heavy	100	-0.005	(-1.09)	0.165	0.014	(2.79)	0.403	0.168	0.082	(16.34)	0.442	0.139
	500	-0.001	(-0.22)	0.073	-0.015	(-2.92)	0.162	0.201	0.022	(4.42)	0.170	0.182
	1000	0.001	(0.23)	0.052	0.000	(-0.07)	0.121	0.187	0.026	(5.28)	0.125	0.176
	2000	0.000	(0.07)	0.036	-0.006	(-1.28)	0.083	0.186	0.016	(3.30)	0.084	0.184
				γ ̂: Co	efficient or	ı Uncens	ored Z					
Light	100	0.006	(2.22)	0.203	0.004	(1.52)	0.207	0.959	0.012	(4.83)	0.206	0.971
	500	0.000	(0.05)	0.090	0.000	(-0.18)	0.091	0.963	0.008	(3.00)	0.091	0.974
	1000	-0.002	(-0.95)	0.064	-0.003	(-1.35)	0.065	0.971	0.005	(1.93)	0.065	0.971
	2000	-0.002	(-0.79)	0.045	-0.003	(-1.30)	0.045	0.972	0.005	(2.00)	0.045	0.992
Heavy	100	0.006	(2.22)	0.203	0.002	(0.89)	0.210	0.935	0.016	(6.53)	0.207	0.957
	500	0.000	(0.05)	0.090	-0.002	(-0.67)	0.092	0.939	0.012	(4.90)	0.091	0.964
	1000	-0.002	(-0.95)	0.064	-0.003	(-1.38)	0.065	0.960	0.010	(4.11)	0.065	0.962
	2000	-0.002	(-0.79)	0.045	-0.004	(-1.74)	0.046	0.924	0.010	(4.00)	0.045	0.978
Extra Heavy	100	0.006	(2.22)	0.203	-0.001	(-0.34)	0.248	0.669	0.028	(11.25)	0.212	0.917
	500	0.000	(0.05)	0.090	-0.005	(-1.91)	0.107	0.701	0.024	(9.79)	0.093	0.926
	1000	-0.002	(-0.95)	0.064	-0.008	(-3.02)	0.075	0.713	0.022	(8.75)	0.067	0.907
	2000	-0.002	(-0.79)	0.045	-0.010	(-3.85)	0.053	0.703	0.022	(8.96)	0.045	0.964

Note: Bias (%): empirical bias (empirical percent bias); SE: empirical standard error; RE: empirical relative efficiency to the full-cohort analysis. The censored covariate X was generated from a log-normal distribution with mean = 0.05Z and variance = 0.25 (on the log scale). All other variables were generated as in Section 3.1. True parameter values were $(\alpha, \beta, \gamma) = (1, 0.5, 0.25)$. The MLE for the Weibull extension converged in $\geq 99.8\%$ of replicates of imputation in each setting (just 3 of 12,000 total replicates did not converge); all other entries are based on 1000 replicates.

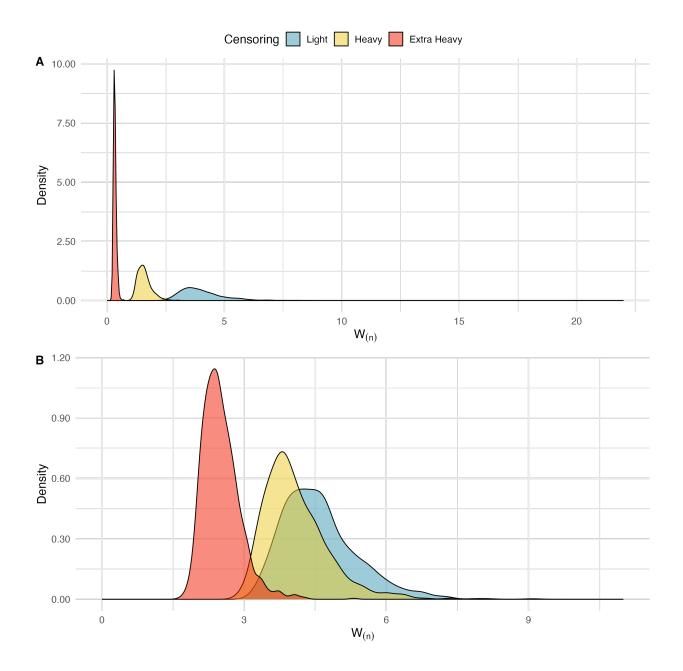


Figure S8: Due to the Weibull distribution's skewness, higher censoring rates led to smaller values of $W_{(n)}$ (the maximum of the observed covariate), which led to worse performance (i.e., higher bias) when calculating the conditional mean with the trapezoidal rule. **A** and **B** are the empirical densities of $W_{(n)}$ when X was generated from a Weibull and a log-normal distribution, respectively, under light, heavy, or extra heavy censoring.

Web Appendix C Additional Results from the PREDICT-HD Analysis

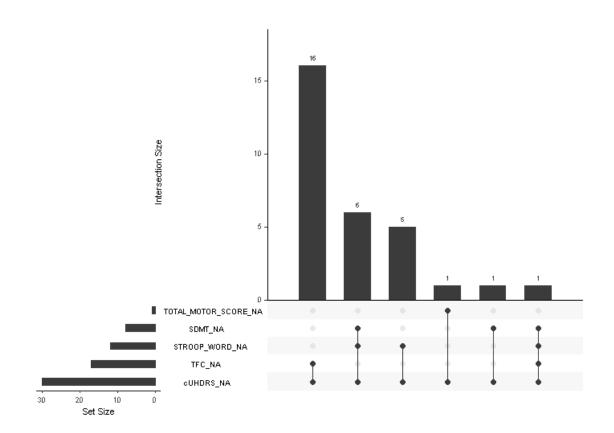


Figure S9: Patterns of missing data in the outcome cUHDRS (composite Unified Huntington Disease Rating Scale) and its component variables total functional capacity (TFC), total motor score (TOTAL_MOTOR_SCORE), Symbol Digit Modality Test (SDMT), and Stroop Word Reading Test (STROOP_WORD) at study entry. This plot was created using the **naniar** package (Tierney et al., 2021).

Web Appendix C.1 Details About Imputing Censored Times to Diagnosis

Imputation began by modeling the conditional survival function for TIME₀ given other fully observed covariates from study entry. First, we fit the Cox proportional hazards model for $h_{\lambda}(\text{TIME}_{0}|\text{AGE}_{0}, \text{CAG}_{0}) = \lambda_{0}(\text{TIME}_{0}) \exp{(\lambda_{1}\text{AGE}_{0} + \lambda_{2}\text{AGE}_{0} \times \text{CAG}_{0})}$, and tested for proportional

hazards using the coxph and cox.zph functions, respectively, from the survival package (Therneau and Grambsch, 2000). (There was no evidence that the assumption was violated, with both p-values > 0.1.) The covariates AGE_0 and $AGE_0 \times CAG_0$, were chosen to align with the CAP model proxy for time to diagnosis from Zhang et al. (2011). Then, we calculated Breslow's estimator $\hat{S}_0(\text{TIME}_0)$ based on the estimated log hazard ratios $\hat{\lambda}_1 = -0.038$ and $\hat{\lambda}_2 = 0.022$.

With this, we had an estimator $\widehat{S}(\mathtt{TIME}_0|\mathtt{AGE}_0,\mathtt{CAG}_0)$ for values of \mathtt{TIME}_0 up to $\widetilde{X}=11.42$, the longest observed time from study entry to diagnosis in PREDICT-HD. Following from our empirical findings in Section 3.3, we used the Weibull extension to extrapolate the survival estimator beyond the largest uncensored value, where $\widehat{S}_0(t=11.42)=0.89$. While we cannot guarantee that these data follow a Weibull distribution, the added flexibility of this extension over the exponential was appealing. Also, unlike our simulations, the context of \mathtt{TIME}_0 could be used to refine the upper bound of the integral in Equation (1). Specifically, \mathtt{TIME}_0 from study entry to clinical Huntington's disease diagnosis could not be infinite for the simple reason that humans are not immortal. Instead, we assumed \mathtt{TIME}_0 of diagnosis would be no longer than 60 years from study entry. Additional details are in Web Appendix A.3.

Web Appendix C.2 Comparing Imputed Times to Diagnosis

Empirical densities of observed and imputed TIME₀ from study entry to clinical Huntington's disease diagnosis for the two imputation approaches exhibited some distinct differences (Figure S10). Using adaptive quadrature for imputation led to a smooth, unimodal density, with a peak not long after the largest uncensored value of $\tilde{X} = 11.42$ years from study entry to diagnosis. Imputing using the trapezoidal rule instead led to a more volatile density that peaked earlier, at around 10 years to diagnosis. Interestingly, the trapezoidal rule led to a higher maximum of 45 years to diagnosis versus 29 years with adaptive quadrature, but other quantiles were similar (e.g., within 4 years). We also noted differences between the densities of TIME₁ from the last visit to clinical Huntington's disease diagnosis (Figure S11), with adaptive quadrature still leading to more support for larger values of TIME₁, representing longer pre-diagnosis follow-up.

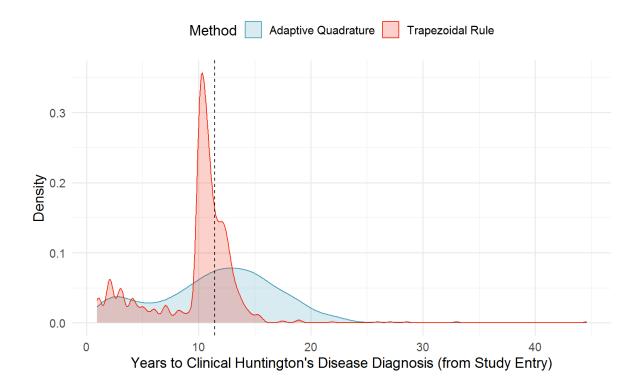


Figure S10: Histograms of observed and imputed times from study entry to Huntington's disease diagnosis in the PREDICT-HD study. The dashed line denotes the longest uncensored value observed in the data, $\tilde{X}=11.42$ years from study entry to diagnosis.

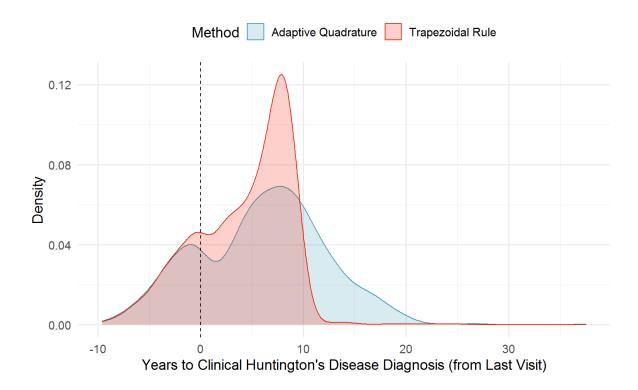


Figure S11: Histograms of observed and imputed times from last visit to Huntington's disease diagnosis in the PREDICT-HD study. The dashed line denotes the time of diagnosis.

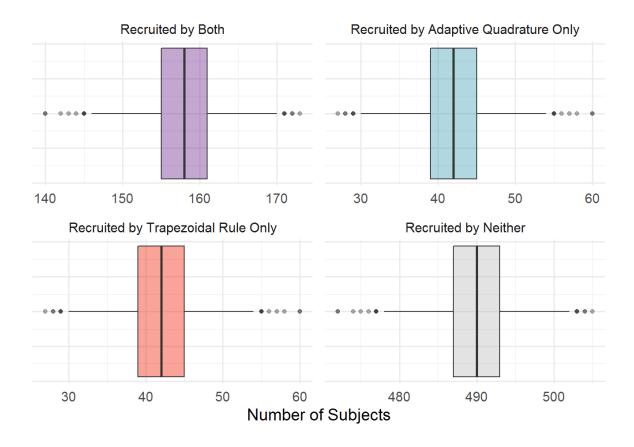


Figure S12: Statuses of n = 732 resampled subjects considered for recruitment into a hypothetical clinical trial based on Huntington's disease symptom progression models using the two imputation approaches in PREDICT-HD. New datasets of n = 732 subjects were created by resampling from censored subjects in PREDICT-HD with replacement 1000 times.

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