

A quantile regression estimator for censored data

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We propose a censored quantile regression estimator motivated by unbiased estimating equations. Under the usual conditional independence assumption of the survival time and the censoring time given the covariates, we show that the proposed estimator is consistent and asymptotically normal. We develop an efficient computational algorithm which uses existing quantile regression code. As a result, bootstrap-type inference can be efficiently implemented. We illustrate the finite-sample performance of the proposed method by simulation studies and analysis of a survival data set.

Keywords: accelerated failure time model; censored quantile regression; Kaplan–Meier estimate; quantile regression

1. Introduction

Censored data arise frequently in biomedical, psychological, social studies and many other applied fields (Kalbfleisch and Prentice [7]). Analysis of such data is complicated by censoring, where an object's time-to-death or other end-point of interest is known to occur only in a certain period of time.

Denote T as the survival time and $C \leq \mathcal{T}_0$ as the censoring time, where \mathcal{T}_0 is the largest follow-up study time. The typical censored data set consists of independent observations (Y_i, δ_i, Z_i) , $i = 1, \dots, n$, where $Y_i = \min(T_i, C_i)$ is the observed failure time; $\delta_i = I(T_i \leq C_i)$ is the censoring indicator; and Z_i is a p -dimensional covariate vector including an intercept. The accelerated failure time model (AFT), specified as $T_i = \beta^T Z_i + \varepsilon_i$ with ε_i , $i = 1, \dots, n$, following a common distribution independently, was studied in a number of papers (Jin *et al.* [5]; Zeng and Lin [26]). However, the assumption made for the AFT model precludes error heteroscedasticity and will yield biased results when it is inappropriate.

Quantile regression introduced by Koenker and Bassett [10] has become an increasingly important tool in statistical analysis. Contrary to the usual model for the conditional mean, it provides distributional information on the dependence of T on Z . A comprehensive review can be found in Koenker [8]. The usefulness of quantile regression in survival analysis was discussed by Koenker and Geiling [11]. The τ th conditional quantile function of the dependent variable T given covariates Z , $Q_T(\tau|Z)$, is defined as $Q_T(\tau|Z) = \inf\{v: F_0(v|Z) \geq \tau\}$, where F_0 is the cumulative conditional distribution function of T given Z . Correspondingly, a quantile regression

model for $Q_T(\tau|Z)$ with $\tau \in (0, 1)$ can be denoted as

$$Q_T(\tau|Z) = \beta'_\tau Z. \quad (1)$$

Note that the AFT model is a special case of this model when β_1 , the coefficient corresponding to the intercept, is quantile dependent, but the other coefficients in β are quantile independent. Another example is the location-scale model $T_i = \alpha_1^T Z_i + (\alpha_2^T Z_i)\varepsilon_i$ in which $\beta = \alpha_1 + \alpha_2 F_\varepsilon^{-1}(\tau)$ when ε_i is independent of Z_i , and F_ε is the distribution function of ε_i .

When data are subject to censoring, statistical estimation and inference for quantile regression is more involved. Indeed, a naive procedure which completely ignores censoring may give highly biased estimates (Koenker [8]). The situation is more complicated if censoring time depends on the covariates. In Section 5, we present the Colorado Plateau uranium miners cohort data (Lubin *et al.* [14], Langholz and Goldstein [12]), where the major interest of this study is to assess the effect of smoking and radon exposure on the rate of median death time of lung cancer. It is found that the censoring time is highly correlated with the covariates. Ignoring this dependence may yield biased estimates; see the Numerical Study section for examples.

Powell [19,20] first studied censored quantile regression with fixed censoring. For random censoring, Ying, Jung and Wei [25] (YJW) proposed a semiparametric median regression model. Despite the simplicity of the method in YJW, this procedure requires the unconditional independence of the survival time and censoring time. This assumption is often restrictive as conditional independence, given the covariates, is more natural (Kalbfleisch and Prentice [7]). In addition, the estimating equation approach proposed in YJW involves solving non-monotone discrete equations, creating difficulty for optimization. As a consequence, inferential procedures such as the resampling approach in Jin, Ying and Wei [6], or the bootstrap method, can be prohibitive computationally. See also Leon, Cai and Wei [13] for a generalization of this method to partly linear models.

Relaxing the independence condition to conditional independence, Portnoy [17] and Neocleous, Vanden Brandan and Portnoy [15] developed a novel estimating approach motivated by the classical Kaplan–Meier estimator in the one sample analysis. Using the martingale representation, Peng and Huang [16] studied another censored quantile regression estimator motivated by the Nelson–Aalen estimator. However, a major shortcoming of Portnoy and Peng and Huang’s methods is that a global linear assumption has to be made, even for estimating the quantile coefficient at a single quantile. To relax this assumption, Wang and Wang [22] recently proposed an innovative redistribution of mass idea, which employs local weighting.

Motivated by the unbiased estimating equation for the quantile regression (Ying *et al.* [25]), we propose a new quantile regression estimator. Under the usual conditional independence assumption of T and C given Z , we show that the proposed estimator is consistent and asymptotically normal. We develop an efficient algorithm which utilizes existing quantile regression code for estimation. The efficient code enables us to use the bootstrap procedure for statistical inference. Our method provides an alternative to Wang and Wang’s locally weighted censored quantile regression. However, the framework proposed by Ying *et al.*, and used by us, may be conceptually simpler.

The rest of the paper is organized as follows. Section 2 discusses the new estimator and the fast computing algorithm. Section 3 provides the theoretical results of the new estimator. Some

numerical studies are presented in Section 4. A data analysis is provided in Section 5. Some concluding remarks are given in Section 6. All the proofs are relegated to the [Appendix](#). When no confusion arises, the dependence of β on τ is suppressed.

2. Censored quantile regression

To estimate β_τ in (1) for the τ th quantile, we propose to solve the following estimating equation:

$$M_n(\beta) = \sum_{i=1}^n Z_i \left[\frac{I(Y_i - \beta' Z_i \geq 0)}{\hat{G}(\beta' Z_i | Z_i)} - (1 - \tau) \right] \approx 0, \tag{2}$$

where $I(\cdot)$ is the indicator function, and \hat{G} is the Kaplan–Meier estimate for $G_0(\cdot | Z_i)$, the conditional survival function of the censoring variable C given the covariates. The estimating equation in (2) is motivated by the fact that $E[I(Y_i - \beta' Z_i \geq 0) | Z_i] = (1 - \tau)G_0(\beta' Z_i | Z_i)$ using the conditional independence of T_i and C_i given Z_i . YJW assumes that $G_0(\beta' Z_i | Z_i) = G_0(\beta' Z_i)$, and our formulation is an extension of YJW’s median regression to quantile regression by allowing G_0 to depend on Z . To solve (2), we need to find its root. Ying *et al.* [25] proposed to minimize $\|M_n(\beta)\|$, a discrete and non-monotone function. Computational complication naturally arises. Ying *et al.* proposed to use the simulated annealing algorithm, or simply the bisection algorithm, to solve the estimating equation, which is computationally demanding. Another complication arises in statistical inference. Since the sampling distribution of the solution involves the unknown density functions of the data, resampling-based approaches are effective tools for conducting statistical inference (Jin, Lin, Wei and Ying [5]). However, inference procedures via these methods would be computationally even more intensive than point estimation, due to the lack of an efficient algorithm.

We start by proposing a new algorithm to solve (2). First note that we can write the estimating equation in (2) as

$$M_n(\beta) = \sum_{i=1}^n \frac{Z_i}{G_i} [I(Y_i - \beta' Z_i \geq 0) - (1 - \tau)] - (1 - \tau) \sum_{i=1}^n \frac{Z_i}{G_i} (G_i - 1),$$

where we write $\hat{G}(\beta' Z_i | Z_i)$ for a preliminary estimate of β as G_i for brevity. In practice, we set $I(Y_i - \beta' Z_i \geq 0) / G_i = 0$ if $G_i = 0$ as recommended by Ying *et al.* [25]. The solution to this function is the minimizer of the following linear programming problem:

$$S_n(\beta) = \sum_{i=1}^n G_i^{-1} \{ \rho_\tau(Y_i - \beta' Z_i) + \rho_\tau(Y_i^* - \beta' Z_i (G_i - 1)) \}, \tag{3}$$

where $\rho_\tau(s) = s[I(s \geq 0) - (1 - \tau)]$ is the check loss function used in quantile regression, and Y_i^* is a small constant less than $-\beta' Z_i (G_i - 1)$ for all β ’s in a compact space. In this paper, we set $Y_i^* = Y^* = \min\{Y_i\} - A$ with $A = 200$. This new formulation suggests that the fast quantile regression code (Portnoy and Koenker [18], Koenker [8]) can be directly used to solve the censored quantile regression defined by (2). We note that Yin and Cai [23] used the Nelder–Mead

simplex algorithm when T and C are independent. The simplex algorithm is generally much slower than the interior point algorithm specially developed for quantile regression (Portnoy and Koenker [18]).

For estimating the weighting function $G_0(\beta'Z_i|Z_i)$, we propose to use the local Kaplan–Meier estimator $\hat{G}(\beta'Z_i|Z_i)$. To be specific, $G_0(\cdot|Z_i)$ is estimated by

$$\hat{G}(t|z) = \prod_{j=1}^n \left[1 - \frac{B_{nj}(z)}{\sum_{k=1}^n I(Y_k \geq Y_j) B_{nk}(z)} \right]^{I(Y_j \leq t, \delta_j=0)}, \tag{4}$$

where $B_{nj}(z)$ is a sequence of non-negative weights adding up to 1. When $B_{nj}(z) = 1/n$ for all j , $\hat{G}_0(t|z)$ reduces to the classical Kaplan–Meier estimator of the survival function in the one-sample case. Following the idea of Wang and Wang [22], we use

$$B_{nj}(z) = K\left(\frac{z - z_j}{h_n}\right) \left[\sum_{k=1}^n K\left(\frac{z - z_k}{h_n}\right) \right]^{-1}, \tag{5}$$

where $K(\cdot)$ is a density function, and $h_n > 0$ is the bandwidth. This is the familiar kernel estimator for the survival function discussed, for example, in Gonzalez-Manteiga and Cadarso-Suarez [4]. When Z is multi-dimensional, we can use the product kernel. For example, in the bivariate case, we can use $K(z_1, z_2) = K_1(z_1)K_2(z_2)$ where $K_1(\cdot)$ and $K_2(\cdot)$ are both univariate kernel functions. In this article, we use the bi-quadratic kernel, defined as $K(s) = \frac{15}{16}(1 - s^2)^2 I(|s| \leq 1)$, which is also used by Wang and Wang [22]. Alternatively, we may use a multivariate density function, for example, from the multivariate normal distribution (Fan and Gijbels [3]).

Since $\hat{G}(\beta'Z_i|Z_i)$ depends on the unknown parameter β , we propose the following iterative algorithm between solving for $\hat{\beta}$ and $\hat{G}(\beta'Z_i|Z_i)$, while the other one is fixed:

1. Given an initial estimate of β denoted as $\beta^{(0)}$, set $k = 0$.
2. Estimate $G_0(Z_i'\beta^{(k)}|Z_i)$ as G_i using the local Kaplan–Meier estimator. Minimize $S_n(\beta)$ in (3) to obtain $\beta^{(k+1)}$.
3. Set $k \leftarrow k + 1$. Go to Step 2 until a convergence criterion is met.

For the initial estimate, we use a similar method as in (Yin and Cai [23]) to solve the following monotone estimating function:

$$\sum_{i=1}^n \frac{\delta_i}{\hat{G}(Y_i|Z_i)} Z_i [I(Y_i - \beta^T Z_i \geq 0) - (1 - \tau)],$$

where $\hat{G}(Y_i|Z_i)$ is the local Kaplan–Meier estimator. This estimator can be seen as the inverse probability weighted quantile regression function (Bang and Tsiatis [1]). Similarly to (Yin and Cai [23]), consistency of $\beta^{(0)}$ can be shown, and convergence of the solution series $\{\beta^{(k)}\}$ follows by the method of induction. Note that, although the initial estimate is also reasonable, its efficiency is adversely affected by the fact that only non-censored observations are used.

Remark 1. We note that our estimator requires estimating $G_0(\beta'Z_i|Z_i)$. In comparison, Wang and Wang [22] estimated the conditional cumulative distribution function of the survival time T_i , evaluated at C_i , given the covariate Z_i . Both estimators use local Kaplan–Meier estimation. Since both methods are estimation equation based approaches, which one is more efficient is likely dependent on the particular problem under analysis. We observe empirically that the proposed method performs satisfactorily even if the censoring rate is reasonably low. Of course, if the censoring rate is very low, the proposed method ultimately suffers due to the low sample size used for the local Kaplan–Meier estimate.

We briefly discuss the computation issue before presenting the asymptotic results. The estimation problem in (3) is essentially weighted quantile regression after the weights $G_0(Z_i'\beta|Z_i)$ are estimated using the local Kaplan–Meier method. This method can be easily implemented by extending the Kaplan–Meier estimate for the survival function of C . In particular, we augment observations $(Y_i^*, Z_i(G_i - 1))$ with weights $1/G_i$ to the existing data set (Y_i, Z_i) with weight $1/G_i$. We then apply function *rq* in R library *quantreg* on the augmented data set using the weights to fit a regular quantile regression model. This process has to be iterated since β in $G_0(Z_i'\beta|Z_i)$ is unknown. The iteration is initialized by using the inverse probability estimator. For the examples in the simulation part and the data analysis, this iteration is very fast. Convergence is achieved usually in a few iterations for a reasonable convergence criterion. Note that we need to estimate $G_0(Z_i'\beta|Z_i)$ at each iteration, while no iteration is needed for Wang and Wang's algorithm.

3. Asymptotic theory

We establish the consistency and the asymptotic normality of the estimator in this section. To derive the asymptotic properties of the proposed estimator, we require the following regularity assumptions. For convenience, we write the true value of β as β_0 . The regularity conditions are listed as follows:

- C1. T and C are conditionally independent given the covariate Z .
- C2. The true value β_0 of β is in the interior of a bounded convex region \mathcal{B} . The support \mathcal{Z} of Z is bounded.
- C3. $\inf_{Z \in \mathcal{Z}} P(Y \geq T|Z) \geq \eta_0 > 0$, where $T = T_0 \vee \sup_{Z \in \mathcal{Z}, \beta \in \mathcal{B}} Z'\beta$.
- C4. The conditional density functions $f_0(t|z)$ and $g_0(t|z)$ of the failure time T and C , respectively, are uniformly bounded away from infinity and have bounded (uniformly in t) second order partial derivatives with respect to z .
- C5. The bandwidth h_n satisfies $h_n = O(n^{-\nu})$ with $0 < \nu < 1/2$.
- C6. The kernel function $K(\cdot) \geq 0$ is compactly supported and satisfies the Lipschitz condition of order 1, $\int K(u) = 1$, $\int uK(u) du = 0$, $\int K^2(u) du < \infty$ and $\int \|u\|^2 K(u) du < \infty$.
- C7. For β in a neighborhood of β_0 , $E[ZZ'f_0(Z'\beta|Z)]$ is positive definite.

Assumptions C1–C4 are standard in survival analysis. Assumption C5 is needed to ensure the consistency of the local Kaplan–Meier estimator. Assumption C6 is routinely made in nonparametric smoothing, and assumption C7 ensures a unique solution for the limiting estimating equation in the neighborhood of β_0 and is used to derive the asymptotic properties of the estimator.

Intuitively, if $\hat{G}(\beta'Z_i|Z_i)$ is a reasonable estimator of $G(\beta'Z_i|Z_i)$, the consistency of $\hat{\beta}$ follows from the unbiasedness of the estimating equation (2). Formally, we have the following results for the consistency of the estimator.

Theorem 1 (Consistency). *Under conditions C1–C7, we have that $\hat{\beta}_n \rightarrow \beta_0$ in probability as $n \rightarrow \infty$.*

The proof of this theorem uses the uniform consistency of \hat{G} as an estimator of G and is similar to that in Ying *et al.* [25]. Since the criterion function is not smooth, we make use of the general theorem developed by Chen, Linton and Van Keilegom [2] to show the asymptotic normality of the resulting estimator.

Theorem 2 (Asymptotic normality). *Under conditions C1–C7, if $1/4 < v < 1/3$, then we have that*

$$n^{1/2}(\hat{\beta}_n - \beta_0) \xrightarrow{d} N(0, \Gamma_1^{-1} V \Gamma_1^{-1}),$$

where $\Gamma_1 = EZZ'f_0(Z'\beta_0|Z)$ and $V = \text{cov}(V_i)$ with V_i defined in Lemma A.3 in the Appendix.

Note that this theorem is only for problems with a single covariate. As in Wang and Wang [22], we observe that the results are not very sensitive to h_n . In practice, we can use K -folds cross validation to choose the bandwidth. This approach works by dividing the data set in K parts, which are about equally sized. For the k th part, we use the rest $K - 1$ parts of the data to fit the model, and then evaluate the quantile loss from predicting the τ th conditional quantile of T on the uncensored data that are left out. Averaging over $k = 1, \dots, K$, we choose the h that gives the minimum average quantile loss.

The matrices Γ_1 and V in the limiting covariance matrix depend on the unknown conditional density function $f_0(\cdot|z)$ and $g_0(\cdot|z)$. For censored data, they may not be estimated well nonparametrically with finite sample. Thus we use the bootstrap resampling procedure for inference. The validity of this procedure can be shown following Jin *et al.* [5]. We note that for the bootstrap or other resampling methods to be feasible computationally, efficient algorithms are instrumental because a large number of bootstrap replications are needed.

4. Numerical study

For simulation study, we compare the estimator of Ying *et al.* (YJW), the proposed estimator (CQR), the locally weighted censored quantile regression estimator (Lcrq) in Wang and Wang [22], the estimator in Portnoy [17], abbreviated as Port, and the estimator by Peng and Huang [16], abbreviated as PH. We use Wang and Wang's code, available on their websites, for Lcrq and function *crq* in R library *quantreg* for Portnoy's and Peng and Huang's method. YJW is implemented via the iterative method in this paper by replacing $\hat{G}(\beta'Z_i|Z_i)$ in (2) by $\hat{G}(\beta'Z_i)$, which is the Kaplan–Meier estimate for the survival function of C . We follow Yin and Cai [23] and Zhou [27] to obtain the initial value of β by using weights $\hat{G}(Y_i)$ in (2). A justification of this algorithm can be found in Yin and Cai [23]. Note that the local Kaplan–Meier estimate

$\hat{G}(\beta'Z_i|Z_i)$ can be obtained by simply modifying Wang and Wang's R function for their local Kaplan–Meier estimation.

We compare the mean bias (MB), the median absolute error (MAE) and the root mean square errors (RMSE) of these procedures (Koenker [9]). We fix $h = 0.05$ for all the simulations as suggested by Wang and Wang [22]. Other choices of the bandwidth were also tried. The results are similar and are omitted to save space. We investigate the performance at the median $\tau = 0.5$ for two sample sizes $n = 100$ and 200 . For Examples 1 and 2, we have also examined the performance at $\tau = 0.7$, and the results are similar. For each setup, the simulation is repeated 500 times. And we use 400 bootstrap replications for inference.

Example 1. We take the first example from Wang and Wang [22] to generate failure time from the following i.i.d. error model

$$T_i = b_0 + b_1 z_i + \varepsilon_i, \quad i = 1, \dots, n,$$

where $b_0 = 3$, $b_1 = 5$, $Z \sim U(0, 1)$ and $\varepsilon_i = \eta_i - \Phi^{-1}(\tau)$ with $\{\eta_i\}_{i=1}^n$ being i.i.d. standard normal random variables. The censoring variable is either generated from $U(0, 14)$ or $U(0, 36)$ such that about 40% or 15% of the observations are censored at the median, when $\tau = 0.5$ is used for generating ε .

Example 2. This example is again taken from Wang and Wang [22]. The data are generated from

$$T_i = b_0 + b_1 z_i + (0.2 + a(z_i - 0.5)^2)\varepsilon_i, \quad i = 1, \dots, n,$$

where $b_0 = 2$, $b_1 = 1$, $z_i \sim N(0, 1)$ and $\varepsilon_i = \eta_i - \Phi^{-1}(\tau)$ with $\{\eta_i\}_{i=1}^n$ being i.i.d. standard normal random variables. Here a takes the value 0, 0.5 and 2 to indicate no, median and strong deviation from the global linearity assumption. The censoring variable C_i is generated from $U(0, 7)$ or $U(0, 18)$ to give 40% and 15% censoring at the median for $a = 2$.

Example 3. The model to generate T_i is the same as Example 2 with $b_0 = 1$ and $a = 2$. The censoring variable C_i is generated from a mixture of distributions. Specifically, if $z_i < 1$, C_i is generated from $U(0, 4)$; otherwise, C_i is generated from $U(0, 8)$. This scheme gives about 30% censoring at the median.

Example 4. This model is similar to Example 2 with $a = 2$. However, the censoring time C_i is generated from the following model $C_i = A + b z_i + \eta_i$, $i = 1, \dots, n$, where $b = 0, 0.5, 1$ indicates a different level of dependence of the censoring time on the covariates. The random variable η_i follows the standard normal distribution, and A is either 1.35 or 2.6, such that when $b = 1$, about 40% or 15% observations are censored.

For Examples 1 and 2, the censoring time and the survival time are independent. In Example 1, all the conditional quantiles are linear functions of the covariates. Example 2 gives a model with only the τ th quantile being a linear function when $a \neq 0$. Note that Wang and Wang [22] have shown that Portnoy's approach gives biased estimates for the coefficients when $a = 2$. For Examples 3 and 4, T and C are not independent, but they are conditionally independent given the

covariates. Example 3 uses a mixture distribution to generate censoring time, while in Example 4, a linear dependence of C on the covariates is used. Two different censoring rates are examined for Examples 1, 2 and 4.

It is not difficult to see that the initial estimate $\beta^{(0)}$ is also \sqrt{n} -consistent. However, we observe empirically that it is less efficient than the final estimate after iteration. For example, in Example 2 when $n = 100$, $a = 2$ and censoring rate is 40%, the RMSEs of $\beta^{(0)}$ are 0.438 and 0.697 when censoring rate is 40%, and 0.246 and 0.450 when about 15% of the data are censored. A related comparison was made in Yin, Zeng and Li [24]. The results for the other methods are summarized in Tables 1 and 2 when $\tau = 0.5$ and $n = 100$. The results for $\tau = 0.7$ or $n = 200$ are qualitatively similar and thus are omitted. We have the following observations. First, CQR outperforms YJW in general, especially when the unconditional independence is violated. Second, when the global linearity holds, Port and PH generally outperform CQR and Lcrq, although by a small margin. When the global linearity is mildly violated, PH and Port both perform competitively with CQR and Lcrq. This demonstrates the robustness of PH and Port. However, when this assumption is severely violated, CQR and Lcrq perform better in general, especially in terms of RMSE. However, how much improvement can be expected is likely dependent on a number of factors, such as the censoring mechanism and rates. Third, CQR and Lcrq have similar performance across all the simulations. The difference between these two approaches is usually negligible. Fourth, when the censoring is low (15%), CQR performs competitively compared to Lcrq, indicating its robustness with respect to the required sample size for estimating the local Kaplan–Meier curve. We conclude that when the global linearity is violated, and C is not unconditionally independent of T , the proposed method is preferred over YJW, Port and PH.

We assess the performance of the bootstrap inference procedure by comparing it to the bootstrap percentile inference procedure developed in Wang and Wang [22]. For brevity, we only report the result for Example 2 when $a = 2$, and the censoring rate is 40%, and for Example 3. We record the empirical coverage probability (ECP) and the empirical mean length (EML) of the resulting confidence intervals in Table 3. The nominal level used is 0.95. For these two examples, both CQR and Lcrq give coverage probabilities close to the nominal level with comparable average empirical lengths.

Since CQR relies on the local Kaplan–Meier estimate, it is of great interest to see how it performs when Z is multi-dimensional. To this end, we use the same model in Example 1, but add independent standard uniform covariates $z^{(2)}, \dots, z^{(d)}$ to z . Thus, the coefficients associated with these additional covariates are zero. We use bandwidth 0.05, 0.1, 0.2, 0.3, 0.4, respectively, when $d = 1, 2, \dots, 5$. In Table 4, we see that with $n = 200$, CQR seems to give unbiased estimates when $d = 1, 2$ and 3 with low censoring 15%. However, it can only be applied up to $d = 2$ if censoring rate is as high as 40%.

5. Data analysis

As an example, we apply the proposed method to the Colorado Plateau uranium miners cohort data (Lubin *et al.* [14], Langholz and Goldstein [12]). The major interest of this study is to assess the effect of smoking on the rate of median lung cancer. This data set consists of 3347 Caucasian male miners who worked underground for at least one month in the uranium mines of

Table 1. Simulation results for Examples 1 and 2

Ex.	c%	a	Bias		MAE		RMSE		
			β_0	β_1	β_0	β_1	β_0	β_1	
1	40%		YJW	0.010	-0.015	0.228	0.431	0.341	0.644
			CQR	-0.007	-0.092	0.211	0.392	0.305	0.583
			Lcqr	-0.009	-0.018	0.196	0.375	0.299	0.554
			Port	-0.042	-0.003	0.198	0.381	0.299	0.548
			PH	0.019	0.005	0.203	0.380	0.299	0.558
	15%		YJW	-0.016	0.023	0.191	0.330	0.293	0.508
			CQR	-0.012	-0.012	0.186	0.317	0.280	0.481
			Lcqr	-0.013	0.005	0.186	0.311	0.281	0.485
			Port	-0.059	0.007	0.179	0.298	0.279	0.469
			PH	0.001	0.007	0.186	0.305	0.277	0.477
2	40%	2	YJW	0.007	-0.009	0.159	0.326	0.249	0.537
			CQR	-0.060	-0.030	0.139	0.267	0.211	0.393
			Lcqr	-0.053	0.008	0.144	0.272	0.215	0.406
			Port	-0.021	-0.010	0.164	0.308	0.224	0.443
			PH	0.058	-0.119	0.166	0.304	0.235	0.460
		0.5	YJW	-0.001	0.012	0.058	0.125	0.089	0.188
			CQR	-0.044	-0.016	0.064	0.106	0.095	0.154
			Lcqr	-0.021	0.009	0.058	0.106	0.088	0.164
			Port	-0.020	0.012	0.058	0.109	0.089	0.168
			PH	0.013	-0.014	0.057	0.106	0.087	0.169
	0	YJW	0.003	0.008	0.022	0.025	0.033	0.040	
		CQR	-0.022	-0.012	0.028	0.024	0.041	0.037	
		Lcqr	-0.004	-0.002	0.021	0.022	0.031	0.034	
		Port	-0.010	0.001	0.021	0.021	0.032	0.033	
		PH	0.003	0.001	0.021	0.021	0.031	0.033	
	15%	2	YJW	-0.006	0.012	0.146	0.292	0.212	0.425
			CQR	-0.024	-0.004	0.134	0.267	0.202	0.393
			Lcqr	-0.023	0.013	0.138	0.271	0.202	0.396
			Port	-0.051	0.039	0.141	0.277	0.214	0.410
			PH	0.021	-0.038	0.143	0.288	0.208	0.406
0.5		YJW	0.001	0.000	0.055	0.100	0.082	0.150	
		CQR	-0.011	-0.008	0.055	0.092	0.082	0.141	
		Lcqr	-0.005	0.000	0.052	0.092	0.081	0.144	
		Port	-0.025	0.014	0.056	0.091	0.085	0.144	
		PH	0.008	-0.008	0.054	0.094	0.081	0.144	
0	YJW	0.001	0.003	0.018	0.019	0.027	0.029		
	CQR	-0.007	-0.003	0.020	0.019	0.028	0.028		
	Lcqr	-0.001	-0.000	0.019	0.018	0.027	0.027		
	Port	-0.011	-0.000	0.020	0.018	0.029	0.027		
	PH	0.001	0.000	0.018	0.018	0.026	0.027		

Table 2. Simulation results for Examples 3 and 4

Ex.	c%	a	Bias		MAE		RMSE		
			β_0	β_1	β_0	β_1	β_0	β_1	
3	30%		YJW	0.035	0.544	0.124	0.482	0.206	0.810
			CQR	0.005	-0.023	0.115	0.223	0.164	0.325
			Lcqr	0.011	0.005	0.109	0.234	0.164	0.333
			Port	0.020	0.017	0.124	0.257	0.190	0.367
			PH	0.088	-0.058	0.128	0.261	0.229	0.388
4	30%	1	YJW	-0.115	0.421	0.121	0.411	0.159	0.473
			CQR	-0.077	0.081	0.095	0.137	0.137	0.217
			Lcqr	-0.080	0.083	0.095	0.138	0.139	0.218
			Port	-0.029	0.024	0.086	0.140	0.131	0.226
			PH	0.017	-0.020	0.085	0.148	0.130	0.222
		0.5	YJW	-0.063	0.227	0.0944	0.228	0.137	0.331
			CQR	-0.055	-0.011	0.090	0.155	0.131	0.217
			Lcqr	-0.051	-0.010	0.090	0.153	0.129	0.222
			Port	-0.018	-0.022	0.093	0.178	0.136	0.251
			PH	0.035	-0.089	0.090	0.189	0.141	0.267
		0	YJW	0.000	-0.020	0.096	0.207	0.143	0.311
			CQR	-0.042	-0.081	0.088	0.191	0.127	0.264
	Lcqr		-0.040	-0.056	0.086	0.199	0.129	0.279	
	Port		-0.020	-0.037	0.088	0.207	0.135	0.306	
	PH		0.030	-0.111	0.092	0.234	0.135	0.319	
	15%	1	YJW	-0.020	0.226	0.079	0.226	0.117	0.323
			CQR	-0.014	0.023	0.078	0.148	0.114	0.215
			Lcqr	-0.015	0.021	0.076	0.146	0.114	0.213
			Port	-0.038	0.029	0.084	0.155	0.125	0.227
			PH	0.007	-0.007	0.078	0.152	0.118	0.223
		0.5	YJW	-0.017	0.157	0.081	0.187	0.123	0.290
			CQR	-0.004	-0.015	0.078	0.141	0.119	0.218
			Lcqr	-0.002	-0.021	0.077	0.144	0.119	0.216
			Port	-0.034	0.008	0.088	0.145	0.130	0.225
PH			0.014	-0.036	0.081	0.143	0.124	0.226	
0		YJW	0.000	-0.001	0.083	0.167	0.123	0.260	
		CQR	-0.000	-0.052	0.080	0.156	0.119	0.235	
	Lcqr	0.000	-0.058	0.079	0.160	0.119	0.237		
	Port	-0.031	-0.021	0.085	0.157	0.126	0.237		
	PH	0.017	-0.077	0.079	0.166	0.123	0.248		

the Colorado Plateau area. In total, there are 258 miners who died of lung cancer. Apart from the failure time, information of the age, the cumulative radon exposure and cumulative smoking in number of packs is available. In our study, we randomly choose 258 miners who are censored and

Table 3. Performance of the inference procedure. For Example 2, only the result for $a = 2$ and 40% censoring is presented

Ex.	n	τ	CQR				Lcrq			
			ECP		EML		ECP		EML	
			β_0	β_1	β_0	β_1	β_0	β_1	β_0	β_1
2	100	0.5	0.948	0.930	0.800	1.541	0.938	0.950	0.806	1.564
		0.7	0.938	0.944	0.862	1.678	0.956	0.954	0.883	1.740
	200	0.5	0.928	0.934	0.533	1.031	0.946	0.938	0.586	1.147
		0.7	0.930	0.932	0.567	1.102	0.934	0.948	0.596	1.174
3	100	0.5	0.910	0.930	0.612	1.195	0.942	0.924	0.596	1.196
		0.7	0.916	0.928	1.037	2.086	0.928	0.936	0.956	1.966
	200	0.5	0.916	0.916	0.423	0.839	0.954	0.950	0.424	0.872
		0.7	0.934	0.928	0.772	1.490	0.946	0.944	0.715	1.445

Table 4. Multi-dimensional covariates when $n = 200$. The standard errors (SE) are reported in parentheses. Note that the SEs of MAE and RMSE are computed via bootstrapping 1000 replications

d	$c\%$	Bias		MAE		RMSE	
		β_0	β_1	β_0	β_1	β_0	β_1
1	40%	-0.010 (0.220)	-0.034 (0.412)	0.152 (0.006)	0.277 (0.009)	0.220 (0.005)	0.413 (0.009)
	15%	0.001 (0.191)	-0.010 (0.342)	0.127 (0.006)	0.227 (0.010)	0.191 (0.005)	0.342 (0.008)
2	40%	-0.070 (0.286)	-0.260 (0.419)	0.199 (0.009)	0.338 (0.012)	0.294 (0.007)	0.493 (0.010)
	15%	-0.027 (0.256)	-0.063 (0.344)	0.177 (0.006)	0.245 (0.007)	0.258 (0.006)	0.350 (0.008)
3	40%	-0.100 (0.355)	-0.339 (0.414)	0.247 (0.009)	0.378 (0.010)	0.369 (0.008)	0.535 (0.011)
	15%	-0.032 (0.314)	-0.096 (0.341)	0.211 (0.008)	0.236 (0.007)	0.315 (0.007)	0.353 (0.007)
4	40%	-0.087 (0.430)	-0.414 (0.438)	0.285 (0.011)	0.452 (0.016)	0.438 (0.011)	0.602 (0.013)
	15%	-0.029 (0.354)	-0.130 (0.334)	0.238 (0.011)	0.229 (0.009)	0.355 (0.007)	0.359 (0.010)
5	40%	-0.089 (0.485)	-0.441 (0.430)	0.364 (0.013)	0.465 (0.019)	0.493 (0.011)	0.616 (0.014)
	15%	-0.048 (0.384)	-0.125 (0.345)	0.254 (0.009)	0.245 (0.009)	0.387 (0.008)	0.367 (0.009)

all the miners who experience the lung cancer. We use this scheme to yield a median censoring scenario, suggested by the simulation studies. This data analysis means to illustrate the difference between different approaches. The scatter plots of the log survival time are presented at the top row of Figure 1. Let Z_1 be the logarithm of the cumulative radon exposure in 100 working level months, Z_2 be the cumulative smoking in 1000 packs and Z_3 be the age at entry to the study. To explore the dependence of the log survival time against these covariates, we fit three separate marginal models using polynomial B-splines to approximate the effects of radon, age and smoking, respectively. In Figure 1, we plot the estimated log survival time against the three covariates at quantiles $\tau = 0.01, 0.05, 0.1, 0.3, 0.5$. Strong non-linearity is present, especially for lower quantiles. When $\tau = 0.5$, the log survival time is approximately linear. These facts suggest that the global linearity assumption may not hold. To further examine whether unconditional independence of the survival time and censoring time is appropriate, we fit the Cox model to the censoring time with respect to the covariates. The two covariates radon and age are both found significant from zero with p -values less than 10^{-3} . This indicates that the unconditional independent assumption needed for YJW may be inappropriate for this data. Graphically, the dependence of the censoring time on the covariates can be seen from Figure 1, where Kaplan–Meier estimates of the survival functions, dichotomized by the median of these covariates, are plotted. From the figure, an observation is more likely to be censored at an earlier time if radon is high, age is young or the subject smoked less. Formal log-rank tests by dichotomizing the covariates also indicate that radon (p -value $< 10^{-3}$) and smoking (p -value 0.03) are highly correlated with the censoring time, while age (p -value 0.08) is not significant. Note that these log-rank tests only investigate these covariates marginally.

Since we have three continuous covariates, we use the three-dimensional kernel after standardizing the covariates, which is the product of three bi-quadratic kernels for radon, smoking and age. We investigate the median log survival time on the three covariates. For Lcrq and CQR, we use the same bandwidth for the three univariate kernels and apply 10-fold cross validation to choose the optimal bandwidth. The results are summarized in Table 5. It is seen that Ying *et al.* estimate age as the only significant variable, while CQR and Lcrq both estimate age and radon as significant variables. The result of Ying *et al.*'s approach in this example is problematic due to the dependence of the censoring time on the covariates. The 95% confidence intervals are obtained by using the bootstrap percentile approach (Wang and Wang [22]) using 1000 bootstrap repetitions. The fact that we only use a random sample for the censored data suggests that the results, especially the numerical ones, should be interpreted with certain caution.

6. Conclusion

We have proposed a novel extension of Ying, Jung and Wei's median regression to quantile regression. Our model is more flexible in that only conditional independence of the survival time and censoring time are assumed. Moreover, we have proposed a new and fast fitting algorithm, applicable to Ying *et al.*'s median regression model, making use of the efficient quantile regression code developed by Koenker. Therefore, resampling based inference procedure can be efficiently implemented. We have compared our estimator to the approaches developed in Portnoy [17], Peng and Huang [16] and Wang and Wang [22]. The simulation results show that the

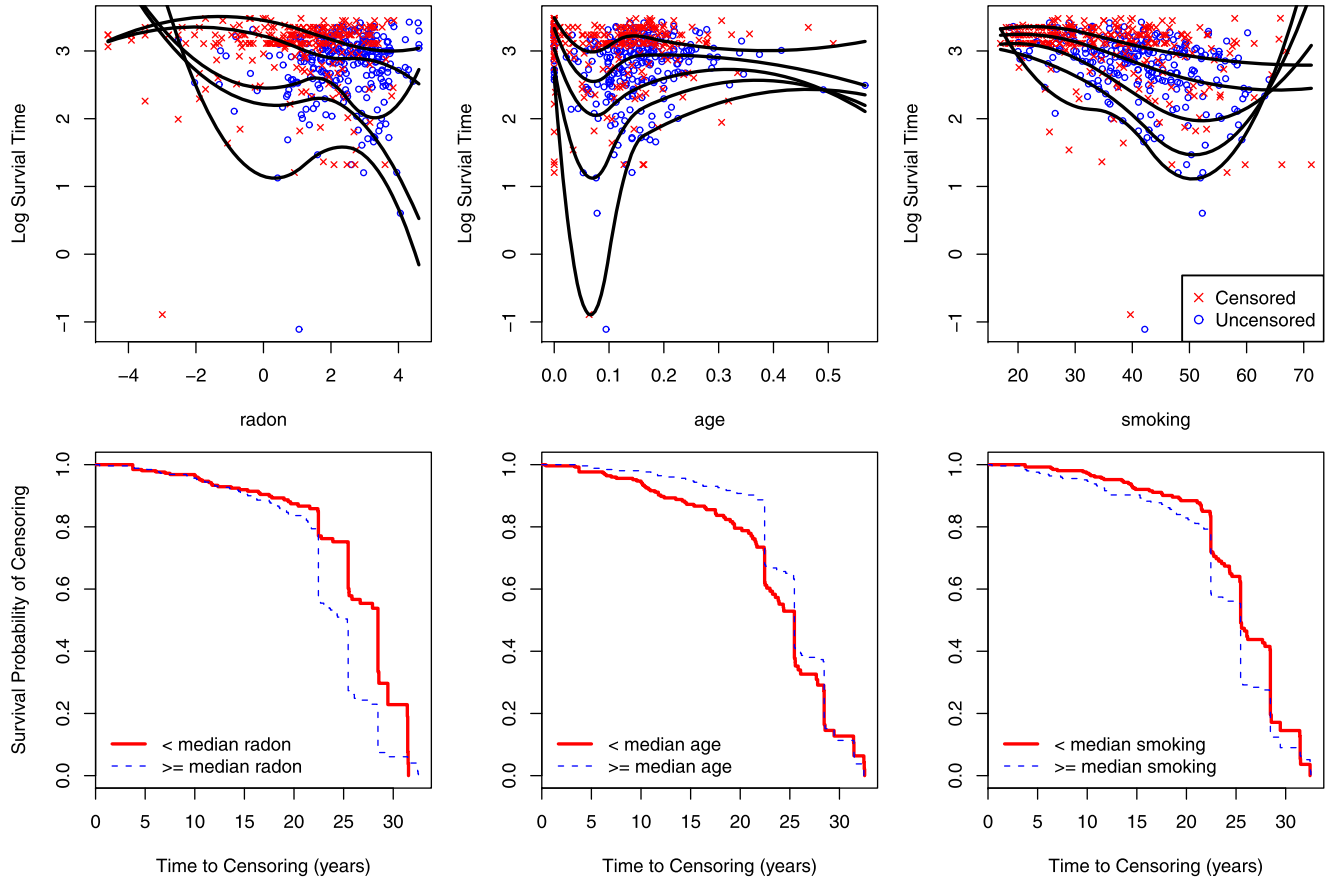


Figure 1. Colorado miners cohort data. Top row: The scatter plots of the log survival time versus the covariates. The marginally fitted log survival times against each covariate at quantiles 0.01, 0.05, 0.1, 0.3, 0.5 (the solid lines from the bottom to the top) are also plotted. Bottom row: The fitted Kaplan–Meier survival curves for the censoring time when covariates are dichotomized.

Table 5. The fitted coefficients of the censored quantile regression at the median and the 95% confidence intervals for the Colorado Plateau uranium miners cohort data

	CQR	YJW	Lcrq
Radon ($\times 10^{-2}$)	-13.05(-28.85, -9.84)	-2.95(-12.4, 3.23)	-25.60(-34.45, -13.55)
Smoking ($\times 10^{-3}$)	-0.38(-3.73, 3.30)	0.04(-5.19, 3.58)	0.65(-4.91, 2.86)
Age	-1.60(-2.27, -1.28)	-2.01(-2.61, -1.44)	-2.12(-2.76, -1.39)

new method is useful and may have certain advantages over the other methods, especially when the global linearity is violated or the unconditional independence of C and T does not hold.

Identifiability remains a serious issue in censored quantile regression, particularly so when τ is close to 1 or 0 (Peng and Huang [16], Wang and Wang [22]). In practice, we recommend to choose τ in the inference range of interest. Another limitation of the current method is the requirement of estimating $G_0(\cdot|Z)$, which inevitably suffers from the curse of dimensionality if Z is multi-dimensional. In this case, it may be more attractive to handle $G_0(\cdot|Z)$ by using, for example, the Cox model or the single-index model. This line of research merits further investigation. Furthermore, the Kaplan–Meier estimates, even for a global one, may be unstable at the right tails. The technique in Zhou [27] may be used to improve the stability of these estimates.

Appendix

For convenience, we write $\|\beta\|$ as the Euclidean norm of a finite dimensional vector β and $\|G(\cdot)\|_\infty$ as the supreme of the absolute value of a function $G(\cdot)$. First, we cite Theorem 2.1 in Gonzalez and Cadarso [4].

Lemma A.1. *Assume that conditions C4–C6 hold, then*

$$\|\hat{G} - G_0\|_\infty = \sup_t \sup_z |\hat{G}(t|z) - G_0(t|z)| = O_p((\log n)^{1/2} n^{-1/2+v/2} + n^{-2v}).$$

A.1. Proof of Theorem 1

Let $\tilde{M}_n(\beta) = \sum_{i=1}^n (\tau - F_0(Z_i' \beta | Z_i)) Z_i$. It follows from the similar arguments as in Ying *et al.* [25] and Lemma A.1 that

$$\sup_{\beta \in \mathcal{B}} n^{-1} |M_n(\beta) - \tilde{M}_n(\beta)| = o(1) \quad \text{a.s.} \tag{A.1}$$

From assumption C7, $A_n(\beta) = \frac{1}{n} \frac{\partial \tilde{M}_n(\beta)}{\partial \beta} = -\frac{1}{n} \sum_{i=1}^n Z_i Z_i' f_0(Z_i' \beta | Z_i)$ is negative definite with probability one for β in a small neighborhood of β_0 . In addition, $\tilde{M}_n(\beta_0) = 0$. Therefore, $n^{-1} \tilde{M}_n(\beta)$ is bounded away from zero. This argument, together with (A.1), yields that $\hat{\beta}_n \rightarrow \beta_0$ in probability as $n \rightarrow \infty$.

A.2. Proof of Theorem 2

To prove Theorem 2, we exploit Theorem 2 in Chen *et al.* [2] by verifying their conditions (2.1)–(2.4), (2.5') and (2.6'). For convenience, write $M_n(\beta, G) = \frac{1}{n} \sum_{i=1}^n m_i(\beta, G)$, where $m_i(\beta, G) = Z_i \{ \frac{I(Y_i \geq Z'_i \beta)}{G(Z'_i \beta | Z_i)} - (1 - \tau) \}$ and the function class \mathcal{G} that involves the true G_0 as the set of G , such that G has a density function g , $\inf_{z \in \mathcal{Z}} G(\mathcal{T}|z) \geq \eta_0$ and $g(\cdot|z)$ is bounded away from infinity uniformly in t and $z \in \mathcal{Z}$. Then $M(\beta, G) = E m_i(\beta, G) = E Z_i \{ \frac{(1 - F_0(Z'_i \beta | Z_i)) G_0(Z'_i \beta | Z_i)}{G(Z'_i \beta | Z_i)} - (1 - \tau) \}$, where the expectation operator is taken with respect to the marginal distribution function of Z_i and thus $M(\beta_0, G_0) = 0$.

Lemma A.2. *For any positive value $\xi_n = o(1)$, we have that*

$$\sup_{\|\beta - \beta_0\| \leq \xi_n, \|G - G_0\|_\infty \leq \xi_n} \|M_n(\beta, G) - M(\beta, G) - M_n(\beta_0, G_0)\| = o_p(n^{-1/2}).$$

Proof. Let $\eta_1 = \sup_{z \in \mathcal{Z}} \|z\|^2 \vee 1$ and $\eta_2 = \sup_{G \in \mathcal{G}, z \in \mathcal{Z}, t \in \mathcal{T}} (f_0(t|z) + g(t|z)) < \infty$ from assumption C4. For any $(\beta, G) \in \mathcal{B} \times \mathcal{G}$ and $(\beta^*, G^*) \in \mathcal{B} \times \mathcal{G}$, we have that $\|m(\beta, G) - m(\beta^*, G^*)\|^2 \leq 2(U_1 + U_2 + U_3)$ where

$$\begin{aligned} U_1 &= \|ZG(Z'\beta|Z)^{-1}(I(Y \geq Z'\beta) - I(Y \geq Z'\beta^*))\|^2 \\ &\leq \eta_3 |I(Y \geq Z'\beta) - I(Y \geq Z'\beta^*)|, \\ U_2 &= \|ZI(Y \geq Z'\beta^*)(G(Z'\beta|Z)^{-1} - G^*(Z'\beta|Z)^{-1})\|^2 \leq \eta_4 \|G - G^*\|_\infty^2, \\ U_3 &= \|ZI(Y \geq Z'\beta^*)(G^*(Z'\beta|Z)^{-1} - G^*(Z'\beta^*|Z)^{-1})\|^2 \leq \eta_5 \|\beta - \beta^*\|^2, \end{aligned} \tag{A.2}$$

where η_3, η_4, η_5 are some positive constants, only depending on η_k ($k = 0, 1, 2$). It follows from (A.2) that $E(\sup_{\|\beta - \beta^*\| \leq \xi_n} U_1) \leq \eta_1 \eta_2 \eta_3 \xi_n$ and that

$$\sup_{\|\beta - \beta_0\| \leq \xi_n, \|G - G_0\|_\infty \leq \xi_n} \|M(\beta, G) - M(\beta^*, G^*)\|^2 \leq \eta_6 \xi_n \tag{A.3}$$

for some constant $\eta_6 \geq 0$ as n is sufficiently large.

Therefore, condition (3.2) of Chen *et al.* [2] holds with $r = 2$ and $s_j = 1/2$. Similarly to the arguments used in (A.2), condition (3.1) in Chen *et al.* [2] can be also verified. Now we verify their condition (3.3). Let $N(\eta, \mathcal{G}, \|\cdot\|_\infty)$ be the covering numbers (van der Vaart and Wellner [21], page 83) for the function class \mathcal{G} under the metrics $\|\cdot\|_\infty$. An application of Theorem 2.7.1 in van der Vaart and Wellner [21] from assumptions C4 and C2 gives that the logarithm of the covering number of \mathcal{G} is bounded by $K\eta^{-1/2}$ for $\eta \leq 1$, where K is some constant, not depending on n . When $\eta \geq 1$, it follows from the definition of covering numbers that $\log N(\eta, \mathcal{G}, \|\cdot\|_\infty) = 0$, which yields that

$$\int_0^\infty \{\log N(\eta^2, \mathcal{G}, \|\cdot\|_\infty)\}^{1/2} d\eta \leq \int_0^1 K^{1/2} \eta^{-1/2} d\eta < \infty.$$

It then follows easily from Theorem 3 of Chen *et al.* [2] that Lemma A.2 holds. □

To apply Theorem 2 in Chen *et al.* [2], we define $\Gamma_1(\beta_0, G_0)$ as the first derivative function of $M(\beta, G_0)$ with respect to β evaluated at $\beta = \beta_0$. For all $\beta \in \mathcal{B}$, we define the functional derivative of $M(\beta, G)$ at G_0 in the direction $[G - G_0]$ as

$$\Gamma_2(\beta, G_0)[G - G_0] = \lim_{\eta \rightarrow 0} \frac{1}{\eta} [M(\beta, G_0 + \eta(G - G_0)) - M(\beta, G_0)].$$

Lemma A.3. *Assume that the conditions in Theorem 2 hold, then*

$$n^{1/2}(M_n(\beta_0, G_0) + \Gamma_2(\beta_0, G_0)[\hat{G} - G_0]) \xrightarrow{d} N(0, V),$$

where $V = \text{cov}(V_i)$ with $V_i = m_i(\beta_0, G_0) - (1 - \tau)Z_i f_Z(Z_i)\psi(Y_i, \delta_i, Z_i'\beta_0, Z_i)$, and

$$\psi(Y_i, \delta_i, t, z) = \int_0^{Y_i \wedge t} \frac{-g_0(s|z) ds}{\{G_0(s|z)\}^2\{1 - F_0(s|z)\}} + \frac{(1 - \delta_i)I(Y_i \leq t)}{G_0(Y_i|z)\{1 - F_0(Y_i|z)\}}.$$

Proof. By the definition of Γ_2 , a direct calculation gives that

$$\Gamma_2(\beta_0, G_0)[G - G_0] = -(1 - \tau)EZ\{G(Z'\beta_0|Z) - G_0(Z'\beta_0|Z)\}/G_0(Z'\beta_0|Z). \tag{A.4}$$

From Theorem 2.3 of Gonzalez-Manteiga and Cadarso-Suarez [4] and the proof of Theorem 2 in Wang and Wang [22], using assumptions C3–C7, we have that

$$\begin{aligned} \hat{G}(t|z) - G_0(t|z) &= \frac{1}{nh_n} \sum_{i=1}^n K\left(\frac{z - Z_i}{h_n}\right) G_0(t|z)\psi(Y_i, \delta_i, t, z) \\ &+ O_p\left(\left(\frac{\log n}{nh_n}\right)^{3/4} + h_n^2\right). \end{aligned} \tag{A.5}$$

Plugging (A.5) into (A.4), using standard change of variables and Taylor expansion arguments, we obtain that $\Gamma_2(\beta_0, G_0)[\hat{G} - G_0] = -(1 - \tau)\frac{1}{n} \sum_{i=1}^n Z_i f_Z(Z_i)\psi(Y_i, \delta_i, Z_i'\beta_0, Z_i) + o_p(n^{-1/2})$. Therefore, we have $n^{1/2}(M_n(\beta_0, G_0) + \Gamma_2(\beta_0, G_0)[\hat{G} - G_0]) = n^{-1/2} \sum_{i=1}^n V_i + o_p(1)$. An application of the central limit theorem gives that

$$n^{1/2}(M_n(\beta_0, G_0) + \Gamma_2(\beta_0, G_0)[\hat{G} - G_0]) \xrightarrow{d} N(0, V).$$

This proves the lemma. □

Proof of Theorem 2. We verify the conditions in Theorem 2 in Chen *et al.* [2]. Their condition (2.1) can be easily verified by the subgradient condition of quantile regression (Koenker [8]). Their conditions (2.4), (2.5') and (2.6) follow directly from Lemma A.1, A.2 and A.3, respectively. From the definition of Γ_1 , we obtain that

$$\Gamma_1 = \Gamma_1(\beta_0, G_0) = \left. \frac{\partial M(\beta, G_0)}{\partial \beta} \right|_{\beta=\beta_0} = -EZZ' f_0(Z'\beta_0|Z),$$

which is negative definite by assumption C7. Thus condition (2.2) in Chen *et al.* [2] holds. By the routine Taylor expansion, we can verify condition (2.3) in Chen *et al.* [2]. Therefore, we obtain that $n^{1/2}(\hat{\beta}_n - \beta_0) \xrightarrow{d} N(0, \Gamma_1(\beta_0, G_0)^{-1} V \Gamma_1(\beta_0, G_0)^{-1})$. The proof is complete. \square

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