

University of Alberta
Department of Mathematical and Statistical Sciences
Technical Report S139

A CENTRAL LIMIT THEOREM FOR NONLINEAR
QUANTILE REGRESSION

Selvakkadunko Selvaratnam²

April 2, 2019

Abstract This technical report contains unpublished material, relevant to the article *Model-Robust Designs for Nonlinear Quantile Regression* (S. Selvaratnam, L. Kong, D.P. Wiens). Equation numbers and bibliographic items refer to those in the article.

Proof of Theorem 1: The experimenter aims to minimize the loss function

$$\mathcal{L}_E(\boldsymbol{\theta}) = \sum_{i=1}^n \rho_\tau[y_i - F(\mathbf{x}_i, \boldsymbol{\theta}_\tau)].$$

An equivalent loss function is (Oberhofer and Haupt 2016, Asymptotic theory for nonlinear quantile regression under weak dependence, *Econometric Theory* 32: 686-713)

$$\mathcal{L}_H(\gamma) = \sum_{i=1}^n \{\rho_\tau[u_i - h_i(\gamma)] - \rho_\tau[u_i]\}, \quad (\text{A.1})$$

where $h_i(\gamma) = F(\mathbf{x}_i, \boldsymbol{\theta}_\tau + (\gamma/\sqrt{n})) - F(\mathbf{x}_i, \boldsymbol{\theta}_\tau)$, $\gamma = \sqrt{n}(\boldsymbol{\theta} - \boldsymbol{\theta}_\tau)$, and $u_i = \delta(\mathbf{x}_i) + \sigma(\mathbf{x}_i)\varepsilon_i$. We expand the function $F(\mathbf{x}_i, \boldsymbol{\theta}_\tau + (\gamma/\sqrt{n}))$ by applying Taylor's expansion

$$F(\mathbf{x}_i, \boldsymbol{\theta}_\tau + (\gamma/\sqrt{n})) = F(\mathbf{x}_i, \boldsymbol{\theta}_\tau) + \mathbf{f}'(\mathbf{x}_i, \boldsymbol{\theta}_\tau) \frac{\gamma}{\sqrt{n}} + o(1).$$

The loss function in (A.1) is equivalent to the following objective function (Yang et al. 2018, Quantile regression for robust inference on varying coefficient partially linear models, *Journal of the Korean Statistical Society* 47: 172-184):

$$\mathcal{L}_T(\gamma) = \sum_{i=1}^n \{\rho_\tau[u_i - \mathbf{f}'(\mathbf{x}_i, \boldsymbol{\theta}_\tau)\gamma/\sqrt{n}] - \rho_\tau[u_i]\}. \quad (\text{A.2})$$

Note the identity of Knight (Knight [17]):

$$\rho_\tau(r - s) - \rho_\tau(r) = -s[\tau - I(r \leq 0)] + \int_0^s [I(r \leq t) - I(r \leq 0)]dt.$$

²Department of Mathematical and Statistical Sciences; University of Alberta, Edmonton, Alberta; Canada T6G 2G1. e-mail: selvarat@ualberta.ca

We apply Knight's identity to (A.2). Thus, we have

$$\begin{aligned}\mathcal{L}_T(\boldsymbol{\gamma}) &= -\sum_{i=1}^n s_{ni} \psi_\tau(u_i) + \sum_{i=1}^n \int_0^{s_{ni}} [I(u_i \leq t) - I(u_i \leq 0)] dt \\ &= Z_{1n}(\boldsymbol{\gamma}) + Z_{2n}(\boldsymbol{\gamma}), \text{ where } s_{ni} = \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \frac{\boldsymbol{\gamma}}{\sqrt{n}},\end{aligned}$$

where

$$\begin{aligned}Z_{1n}(\boldsymbol{\gamma}) &= -\sum_{i=1}^n s_{ni} \psi_\tau(u_i) \text{ and } Z_{2n}(\boldsymbol{\gamma}) = \sum_{i=1}^n Z_{2ni}(\boldsymbol{\gamma}) \text{ for} \\ Z_{2ni}(\boldsymbol{\gamma}) &= \int_0^{s_{ni}} [I(u_i \leq t) - I(u_i \leq 0)] dt.\end{aligned}$$

Let us consider

$$\begin{aligned}E[Z_{1n}(\boldsymbol{\gamma})] &= -\frac{\boldsymbol{\gamma}'}{\sqrt{n}} \sum_{i=1}^n \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) E[\psi_\tau(u_i)] \\ &= -\frac{\boldsymbol{\gamma}'}{\sqrt{n}} \sum_{i=1}^n \{\tau - G[-\delta^*(\mathbf{x}_{(i)})]\} \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \\ &= -\boldsymbol{\gamma}' \frac{\sqrt{n}}{n} \sum_{i=1}^n \{g_\varepsilon(0) \delta^*(\mathbf{x}_{(i)}) + o(1)\} \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \\ &\rightarrow -\boldsymbol{\gamma}' \left\{ \frac{1}{n} \sum_{i=1}^n \delta^*(\mathbf{x}_{(i)}) \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \right\} g_\varepsilon(0) \sqrt{n} \\ &= -\boldsymbol{\gamma}' \left\{ \sum_{i=1}^N \xi_i \delta^*(\mathbf{x}_i) \mathbf{f}(\mathbf{x}_i, \boldsymbol{\theta}_\tau) \right\} g_\varepsilon(0) \sqrt{n} \\ &= -\boldsymbol{\gamma}' \boldsymbol{\mu} g_\varepsilon(0) \sqrt{n}.\end{aligned}$$

Also, we have

$$\begin{aligned}\text{Var}[Z_{1n}(\boldsymbol{\gamma})] &= \sum_{i=1}^n s_{ni}^2 \text{Var}[\psi_\tau(u_i)] \\ &= \boldsymbol{\gamma}' \frac{1}{n} \sum_{i=1}^n G[-\delta^*(\mathbf{x}_{(i)})] \{1 - G[-\delta^*(\mathbf{x}_{(i)})]\} \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \boldsymbol{\gamma} \\ &= \boldsymbol{\gamma}' \frac{1}{n} \sum_{i=1}^n \{\tau - g_\varepsilon(0) \delta^*(\mathbf{x}_{(i)}) + o(1)\} \{1 - \tau + g_\varepsilon(0) \delta^*(\mathbf{x}_{(i)}) + o(1)\} \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \boldsymbol{\gamma} \\ &\rightarrow \boldsymbol{\gamma}' \frac{1}{n} \sum_{i=1}^n \{\tau - g_\varepsilon(0) \delta^*(\mathbf{x}_{(i)})\} \{1 - \tau + g_\varepsilon(\tau) \delta^*(\mathbf{x}_{(i)})\} \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \boldsymbol{\gamma} \\ &= \boldsymbol{\gamma}' \frac{1}{n} \sum_{i=1}^n \left\{ \begin{array}{c} \tau(1-\tau) \\ +(2\tau-1)g_\varepsilon(0)\delta^*(\mathbf{x}_{(i)}) - g_\varepsilon(0)^2\delta^*(\mathbf{x}_{(i)})^2 \end{array} \right\} \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \boldsymbol{\gamma}. \quad (\text{A.3})\end{aligned}$$

Let us consider the second term in braces in (A.3),

$$\begin{aligned}
& \gamma' \frac{1}{n} \sum_{i=1}^n \{(2\tau - 1)g_\varepsilon(0)\delta^*(\mathbf{x}_{(i)})\} \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \gamma \\
&= (2\tau - 1)g_\varepsilon(0)\gamma' \left\{ \frac{1}{n} \sum_{i=1}^n \delta^*(\mathbf{x}_{(i)}) \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \right\} \gamma \\
&= (2\tau - 1)g_\varepsilon(0)\gamma' \left\{ \sum_{i=1}^N \xi_i \delta^*(\mathbf{x}_i) \mathbf{f}(\mathbf{x}_i, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_i, \boldsymbol{\theta}_\tau) \right\} \gamma \\
&= N(2\tau - 1)g_\varepsilon(0)\gamma' \left\{ \frac{1}{N} \sum_{i=1}^N \xi_i \delta^*(\mathbf{x}_i) \mathbf{f}(\mathbf{x}_i, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_i, \boldsymbol{\theta}_\tau) \right\} \gamma \\
&\leq N\gamma'[(2\tau - 1)g_\varepsilon(0)] \max_{1 \leq i \leq N} \{\|\mathbf{f}(\mathbf{x}_i, \boldsymbol{\theta}_\tau)\| \|\xi_i\| \|\gamma\| \frac{1}{N} \sum_{i=1}^N \delta^*(\mathbf{x}_i) \mathbf{f}(\mathbf{x}_i, \boldsymbol{\theta}_\tau)\} \\
&\rightarrow \mathbf{0} \quad [\text{by (5)}].
\end{aligned}$$

Thus, we can conclude

$$\gamma' \frac{1}{n} \sum_{i=1}^n \{(2\tau - 1)g_\varepsilon(0)\delta^*(\mathbf{x}_{(i)})\} \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \gamma \rightarrow \mathbf{0}. \quad (\text{A.4})$$

The third term in braces in (A.3) is

$$\begin{aligned}
& g_\varepsilon(0)^2 \gamma' \left\{ \frac{1}{n} \sum_{i=1}^n \delta^*(\mathbf{x}_{(i)})^2 \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \right\} \gamma \\
&= Ng_\varepsilon(0)^2 \gamma' \left\{ \frac{1}{N} \sum_{i=1}^N \xi_i \delta^*(\mathbf{x}_i)^2 \mathbf{f}(\mathbf{x}_i, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_i, \boldsymbol{\theta}_\tau) \right\} \gamma \\
&= Ng_\varepsilon(0)^2 \gamma' \frac{1}{N} \sum_{i=1}^N \xi_i \delta^*(\mathbf{x}_i)^2 \mathbf{f}(\mathbf{x}_i, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_i, \boldsymbol{\theta}_\tau) \gamma \\
&\leq Ng_\varepsilon(0)^2 \gamma' \max_{1 \leq i \leq N} \{\xi_i \|\mathbf{f}(\mathbf{x}_i, \boldsymbol{\theta}_\tau)\| |\delta^*(\mathbf{x}_i)|\} \|\gamma\| \frac{1}{N} \sum_{i=1}^N \delta^*(\mathbf{x}_i) \mathbf{f}(\mathbf{x}_i, \boldsymbol{\theta}_\tau) \\
&\rightarrow \mathbf{0} \quad [\text{by (5)}].
\end{aligned}$$

So, we have

$$g_\varepsilon(0)^2 \frac{1}{n} \sum_{i=1}^n \delta^*(\mathbf{x}_{(i)})^2 \gamma' \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \gamma \rightarrow \mathbf{0}. \quad (\text{A.5})$$

By using (A.4) (A.5), and (A.3), we obtain

$$\begin{aligned}
\text{Var}[Z_{1n}(\boldsymbol{\gamma})] &\rightarrow \boldsymbol{\gamma}'\tau(1-\tau) \left\{ \frac{1}{n} \sum_{i=1}^n \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \right\} \boldsymbol{\gamma} \\
&\rightarrow \boldsymbol{\gamma}'\tau(1-\tau) E[\mathbf{f}(\mathbf{x}, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}, \boldsymbol{\theta}_\tau)] \boldsymbol{\gamma} \\
&= \boldsymbol{\gamma}'\tau(1-\tau) \mathbf{P}_0 \boldsymbol{\gamma}.
\end{aligned}$$

Therefore, we have

$$Z_{1n}(\boldsymbol{\gamma}) \xrightarrow{\mathcal{D}} -\boldsymbol{\gamma}' \mathbf{w} \text{ where } \mathbf{w} \sim N(\boldsymbol{\mu}_{g_\varepsilon}(0) \sqrt{n}, \tau(1-\tau) \mathbf{P}_0). \quad (\text{A.6})$$

Next, we consider the component $Z_{2n}(\boldsymbol{\gamma})$:

$$Z_{2n}(\boldsymbol{\gamma}) = \sum_{i=1}^n E[Z_{2ni}(\boldsymbol{\gamma})] + \sum_{i=1}^n \{Z_{2ni}(\boldsymbol{\gamma}) - E[Z_{2ni}(\boldsymbol{\gamma})]\}.$$

We have

$$\begin{aligned}
E[Z_{2n}(\boldsymbol{\gamma})] &= \sum_{i=1}^n E[Z_{2ni}(\boldsymbol{\gamma})] \\
&= \sum_{i=1}^n \int_0^{s_{ni}} \left\{ G \left[-\delta_n^*(\mathbf{x}_{(i)}) + \frac{t}{\sigma(\mathbf{x}_{(i)})} \right] - G[-\delta_n^*(\mathbf{x}_{(i)})] \right\} dt \\
&= \sum_{i=1}^n \int_0^{s_{ni}} g_\varepsilon[-\delta_n^*(\mathbf{x}_{(i)})] \frac{t}{\sigma(\mathbf{x}_{(i)})} dt + o(1) \\
&= \frac{1}{2n} \sum_{i=1}^n \frac{g_\varepsilon[-\delta_n^*(\mathbf{x}_{(i)})]}{\sigma(\mathbf{x}_{(i)})} \boldsymbol{\gamma}' \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \boldsymbol{\gamma} + o(1) \\
&\rightarrow \frac{1}{2} g_\varepsilon(0) \boldsymbol{\gamma}' \left\{ \frac{1}{n} \sum_{i=1}^n \frac{1}{\sigma(\mathbf{x}_{(i)})} \mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \right\} \boldsymbol{\gamma} \\
&= \frac{1}{2} g_\varepsilon(0) \boldsymbol{\gamma}' \left\{ \sum_{i=1}^N \xi_i \frac{1}{\sigma(\mathbf{x}_i)} \mathbf{f}(\mathbf{x}_i, \boldsymbol{\theta}_\tau) \mathbf{f}'(\mathbf{x}_i, \boldsymbol{\theta}_\tau) \right\} \boldsymbol{\gamma} \\
&= \frac{1}{2} \boldsymbol{\gamma}' g_\varepsilon(0) \mathbf{P}_1 \boldsymbol{\gamma}.
\end{aligned}$$

Moreover, we have the bound

$$\begin{aligned}
\text{Var}[Z_{2n}(\boldsymbol{\gamma})] &\leq \sum_{i=1}^n E \left\{ \int_0^{s_{ni}} [I(u_i \leq t) - I(u_i \leq 0)] dt \right\}^2 \\
&\leq \sum_{i=1}^n E \left\{ \int_0^{s_{ni}} dt \int_0^{s_{ni}} [I(u_i \leq t) - I(u_i \leq 0)] dt \right\} \\
&= \sum_{i=1}^n E \left\{ \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \frac{\boldsymbol{\gamma}}{\sqrt{n}} \int_0^{s_{ni}} [I(u_i \leq t) - I(u_i \leq 0)] dt \right\} \\
&= \frac{1}{\sqrt{n}} \sum_{i=1}^n \mathbf{f}'(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau) \boldsymbol{\gamma} E \left\{ \int_0^{s_{ni}} [I(u_i \leq t) - I(u_i \leq 0)] dt \right\} \\
&\leq \frac{1}{\sqrt{n}} \sum_{i=1}^n \|\mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau)\| \|\boldsymbol{\gamma}\| E \left\{ \int_0^{s_{ni}} [I(u_i \leq t) - I(u_i \leq 0)] dt \right\} \\
&\leq \left\{ \frac{1}{\sqrt{n}} \max_{1 \leq i \leq n} \|\mathbf{f}(\mathbf{x}_{(i)}, \boldsymbol{\theta}_\tau)\| \right\} \|\boldsymbol{\gamma}\| E[Z_{2n}(\boldsymbol{\gamma})].
\end{aligned}$$

We have $\text{Var}[Z_{2n}(\boldsymbol{\gamma})] \rightarrow 0$. Using $E[Z_{2n}(\boldsymbol{\gamma})] \rightarrow \frac{1}{2} \boldsymbol{\gamma}' g(0) \mathbf{P}_1 \boldsymbol{\gamma}$ and $\text{Var}[Z_{2n}(\boldsymbol{\gamma})] \rightarrow 0$, we can obtain

$$E \left[Z_{2n}(\boldsymbol{\gamma}) - \frac{1}{2} \boldsymbol{\gamma}' g_\varepsilon(0) \mathbf{P}_1 \boldsymbol{\gamma} \right]^2 \rightarrow 0.$$

Therefore, we have

$$Z_{2n}(\boldsymbol{\gamma}) \rightarrow \frac{1}{2} \boldsymbol{\gamma}' g_\varepsilon(0) \mathbf{P}_1 \boldsymbol{\gamma}. \quad (\text{A.7})$$

Because of (A.6) and (A.7), we have

$$Z_n(\boldsymbol{\gamma}) \xrightarrow{\mathcal{D}} Z(\boldsymbol{\gamma}),$$

where $Z(\boldsymbol{\gamma}) = -\boldsymbol{\gamma}' \mathbf{w} + \frac{1}{2} \boldsymbol{\gamma}' g_\varepsilon(0) \mathbf{P}_1 \boldsymbol{\gamma}$ and $\mathbf{w} \sim N(\boldsymbol{\mu} g_\varepsilon(0) \sqrt{n}, \tau(1-\tau) \mathbf{P}_0)$. The convexity of the limiting objective function $Z(\boldsymbol{\gamma})$ ensures the uniqueness of the minimizer $\hat{\boldsymbol{\gamma}} = \frac{1}{g_\varepsilon(0)} \mathbf{P}_1^{-1} \mathbf{w}$. Therefore, we have

$$\sqrt{n}(\hat{\boldsymbol{\theta}}_{n\tau} - \boldsymbol{\theta}_\tau) = \hat{\boldsymbol{\gamma}}_n = \arg \min Z_n(\boldsymbol{\gamma}) \xrightarrow{\mathcal{D}} \hat{\boldsymbol{\gamma}} = \arg \min Z(\boldsymbol{\gamma}).$$

Thus, we have

$$\sqrt{n}(\hat{\boldsymbol{\theta}}_{n\tau} - \boldsymbol{\theta}_\tau - \mathbf{P}_1^{-1} \boldsymbol{\mu}) \xrightarrow{\mathcal{D}} N \left(\mathbf{0}, \frac{\tau(1-\tau)}{g_\varepsilon(0)^2} \mathbf{P}_1^{-1} \mathbf{P}_0 \mathbf{P}_1^{-1} \right),$$

as required. ■