

Supplementary Material to Renewable Composite Quantile Method and Algorithm for Nonparametric Models with Streaming Data

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This supplementary material contains a detailed algorithm for renewable WCQR estimation, the relevant lemmas and technical proofs for the theoretical results.

A Detailed Algorithm for WCQR Estimation

Algorithm A.1 contains details about obtaining the renewable WCQR estimators for $m(x)$ and $\sigma(x)$ from asymmetric models.

B Lemmas and proofs

The proof of Lemma 2 is as follows.

Proof of Lemma 2 Noting that ε is independent with X and $\mathbb{E}[\varepsilon] = 0$, we have

$$E_{WY} := \mathbb{E}[W(X)Y] = \mathbb{E}[W(X)(m(X) + \sigma(X)\varepsilon)] = \mathbb{E}[W(X)m(X)], \quad (\text{B.1})$$

$$E_{WY^2} := \mathbb{E}[W(X)Y^2] = \mathbb{E}[W(X)(m^2(X) + \sigma^2(X))]. \quad (\text{B.2})$$

Algorithm A.1 Renewable WCQR Estimation for $\{(m(x_i), \sigma(x_i))\}_{i=1}^{\bar{q}}$ from Asymmetric Models

Input Set of grid points $G_* = \{x_i\}_{i=1}^{\bar{q}}$, kernel function $K(\cdot)$, node sets G_{x_i} for $x_i \in G_*$, PLI degree l

- 1: Set initial values $N_0 = \hat{E}_{WY,0} = \hat{E}_{WY^2,0} = \hat{f}_{X,0}(x_i) = \hat{S}_{Y|x,0}(y_{ij}) = 0$ for $y_{ij} \in G_{x_i}$ and $x_i \in G_*$
- 2: **for** $t = 1, 2, \dots$ **do**
- 3: Obtain the t -th data batch $\mathcal{D}_t = \{X_{tj}, Y_{tj}\}_{j=1}^{n_t}$
- 4: Select the t -th bandwidth h_t
- 5: $N_t = N_{t-1} + n_t$
- 6: $\hat{E}_{WY,t} = N_{t-1}/N_t \hat{E}_{WY,t-1} + 1/N_t \sum_{j=1}^{n_t} W(X_{tj})Y_{tj}$
- 7: $\hat{E}_{WY^2,t} = N_{t-1}/N_t \hat{E}_{WY^2,t-1} + 1/N_t \sum_{j=1}^{n_t} W(X_{tj})Y_{tj}^2$
- 8: **for** $x_i \in G_*$ **do**
- 9: $\hat{f}_{X,t}(x_i) = N_{t-1}/N_t \hat{f}_{X,t-1}(x_i) + 1/N_t \sum_{j=1}^{n_t} K_{h_t}(X_{tj} - x_i)$,
- 10: For $y_{ij} \in G_{x_i}$, $\hat{S}_{Y|x_i,t}(y_{ij}) = N_{t-1}/N_t \hat{S}_{Y|x_i,t-1}(y_{ij}) + 1/N_t \sum_{j=1}^{n_t} I(Y_{tj} < y_{ij}) K_{h_t}(X_{tj} - x_i)$
- 11: **end for**
- 12: **if** the estimators for $\{(m(x_i), \sigma(x_i))\}_{x_i \in G_*}$ are needed **then**
- 13: Define $\mathcal{I}_l \hat{f}_{X,t}(\cdot) = \sum_{x_i \in G_*} \hat{f}_{X,t}(x_i) L(\cdot, x_i; l, G_*)$
- 14: Define $\mathcal{I}_l \hat{F}_{Y|x_i,t}(\cdot) = \sum_{y_{ij} \in G_{x_i}} \hat{S}_{Y|x_i,t}(y_{ij}) / \hat{f}_{X,t}(x_i) L(\cdot, y_{ij}; l, G_{x_i})$
- for $x_i \in G_*$
- 15: **for** $J \in \{L_\alpha, U_\alpha\}$ **do**
- 16: $\tilde{r}_t(x_i; J) = \int_{\mathbb{R}} y J(\mathcal{I}_l \hat{F}_{Y|x_i,t}(y)) d\mathcal{I}_l \hat{F}_{Y|x_i,t}(y)$ for $x_i \in G_*$
- 17: Define $\mathcal{I}_l \tilde{r}_t(\cdot; J) = \sum_{x_i \in G_*} \tilde{r}_t(x_i; J) L(\cdot, x_i; l, G_*)$
- 18: **end for**
- 19: $\hat{E}_{WL,t} = \int_{I_*} W(x) \mathcal{I}_l \tilde{r}_t(x; L_\alpha) \mathcal{I}_l \hat{f}_{X,t}(x) dx$
- 20: $\hat{E}_{WU,t} = \int_{I_*} W(x) \mathcal{I}_l \tilde{r}_t(x; U_\alpha) \mathcal{I}_l \hat{f}_{X,t}(x) dx$
- 21: $\hat{w}_t = (\hat{E}_{WY,t} - \hat{E}_{WU,t}) / (\hat{E}_{WL,t} - \hat{E}_{WU,t})$
- 22: $\tilde{r}_t(x_i; J_{m, \hat{w}_t}) = \hat{w}_t \tilde{r}_t(x_i; L_\alpha) + (1 - \hat{w}_t) \tilde{r}_t(x_i; U_\alpha)$ for $x_i \in G_*$
- 23: $\tilde{r}_t(x_i; J_{\sigma, 1}) = -\tilde{r}_t(x_i; L_\alpha) + \tilde{r}_t(x_i; U_\alpha)$ for $x_i \in G_*$
- 24: Define $\mathcal{I}_l \tilde{r}_t(\cdot; J_{m, \hat{w}_t}) = \sum_{x_i \in G_*} \tilde{r}_t(x_i; J_{m, \hat{w}_t}) L(\cdot, x_i; l, G_*)$
- 25: $\hat{E}_{Wm^2,t} = \int_{I_*} W(x) \mathcal{I}_l \tilde{r}_t^2(x; J_{m, \hat{w}_t}) \mathcal{I}_l \hat{f}_{X,t}(x) dx$
- 26: $\hat{E}_{Wr^2,t} = \int_{I_*} W(x) \mathcal{I}_l \tilde{r}_t^2(x; J_{\sigma, 1}) \mathcal{I}_l \hat{f}_{X,t}(x) dx$
- 27: $\hat{\theta}_t = \sqrt{(\hat{E}_{WY^2,t} - \hat{E}_{Wm^2,t}) / \hat{E}_{Wr^2,t}}$
- 28: Output $\{\tilde{r}_t(x_i; J_{m, \hat{w}_t})\}_{x_i \in G_*}$ as the estimators of $\{m(x_i)\}_{x_i \in G_*}$
- 29: Output $\{\hat{\theta}_t \tilde{r}_t(x_i; J_{\sigma, 1})\}_{x_i \in G_*}$ as the estimators of $\{\sigma(x_i)\}_{x_i \in G_*}$
- 30: **end if**
- 31: **end for**

By (19), we have

$$\begin{aligned} E_{W_r} &:= \mathbb{E}[W(X)r(X; J)] \\ &= E_{W_Y} \int_{[0,1]} J(\tau) d\tau + E_{W_\sigma} \int_{[0,1]} J(\tau) F_\varepsilon^{-1}(\tau) d\tau. \end{aligned} \quad (\text{B.3})$$

with $E_{W_\sigma} = \mathbb{E}[W(X)\sigma(X)]$. Based on (B.3), we conclude that if C_{m1} holds, then

$$\int_{[0,1]} J(\tau) F_\varepsilon^{-1}(\tau) d\tau = (E_{W_\sigma})^{-1} (E_{W_r} - E_{W_Y}), \quad (\text{B.4})$$

implying

$$\begin{aligned} &\mathbb{E}[W(X)\sigma(X)] \int_{[0,1]} J(\tau) F_\varepsilon^{-1}(\tau) d\tau \\ &= \mathbb{E}[W(X)(r(X; J) - Y)]. \end{aligned} \quad (\text{B.5})$$

Assume that $J_\sigma(\cdot)$ is a weight function satisfying $C_{\sigma 1}$. Then by (19), we have

$$r(x; J_\sigma) = \sigma(x) \int_{[0,1]} J(\tau) F_\varepsilon^{-1}(\tau) d\tau, \quad (\text{B.6})$$

leading to

$$\mathbb{E}[W(X)r^2(X; J_\sigma)] = E_{W_{\sigma^2}} \left(\int_{[0,1]} J_\sigma(\tau) F_\varepsilon^{-1}(\tau) d\tau \right)^2 \quad (\text{B.7})$$

with $E_{W_{\sigma^2}} := \mathbb{E}[W(X)\sigma^2(X)]$. The equality (B.2) implies

$$E_{W_{\sigma^2}} = \mathbb{E}[W(X)(Y^2 - m^2(X))]. \quad (\text{B.8})$$

Combining (B.8) and (B.7), we obtain

$$\left(\int_{[0,1]} J(\tau) F_\varepsilon^{-1}(\tau) d\tau \right)^2 = \frac{\mathbb{E}[W(X)(Y^2 - m^2(X))]}{\mathbb{E}[W(X)r^2(X; J_\sigma)]}. \quad (\text{B.9})$$

□

By Lemma 1, we can obtain the following result.

Lemma B.1 *Let $1 \leq l \leq q - 1$ and $\mathcal{I}_l F_{Y|x}(\cdot)$ be given in (10). With $F_{Y|x}^{(l+1)}(\cdot)$ existing and continuous on $I(G_x) := [\min G_x, \max G_x]$, it holds that*

$$\|\mathcal{I}_l F_{Y|x} - F_{Y|x}\|_{\infty, I(G_x)} \leq \|F_{Y|x}^{(l+1)}\|_{\infty, I(G_x)} |\Delta(G_x)|^{l+1}.$$

For positive integers l and r , denote

$$k_{l,r} = \int_{\mathbb{R}} u^l K^r(u) du. \quad (\text{B.10})$$

The following lemma is useful to deduce the asymptotic properties of $\widehat{F}_{Y|x}^{(l)}(y)$.

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Lemma B.2 *Assuming that $g : \mathbb{R} \rightarrow \mathbb{R}$ and $f_X(\cdot)$ has derivatives up to order $r + 1$, it holds that*

$$\mathbb{E}[g(X) K_h(X - x)] = \sum_{l=0}^r \frac{k_{l,1} h^l}{l!} (gf_X)^{(l)}(x) + O(k_{r+1,1} M_{r+1} h^{r+1}), \quad (\text{B.11})$$

$$\mathbb{E}[g(X) K_h^2(X - x)] = \frac{1}{h} \sum_{l=0}^r \frac{k_{l,2} h^l}{l!} (gf_X)^{(l)}(x) + O(k_{r+1,2} M_{r+1} h^r) \quad (\text{B.12})$$

with $M_{r+1} = \left\| (gf_X)^{(r+1)} \right\|_{I_*, \infty}$.

Proof By Taylor's expansion, we have

$$\begin{aligned} \mathbb{E}[g(X) K_h(X - x)] &= \int_{\mathbb{R}} g(u) f_X(u) K_h(u - x) du \\ &= \int_{\mathbb{R}} (gf_X)(x + vh) K(v) dv \\ &= \sum_{l=0}^r (l!)^{-1} (gf_X)^{(l)}(x) h^l \int_{\mathbb{R}} v^l K(v) dv \\ &\quad + O\left(M_{r+1} h^{r+1} \int_{\mathbb{R}} v^{r+1} K(v) dv\right) \end{aligned} \quad (\text{B.13})$$

leading to (B.11). Similarly, we have

$$\begin{aligned} \mathbb{E}[g(X) K_h^2(X - x)] &= \int_{\mathbb{R}} g(u) f_X(u) K_h^2(u - x) du \\ &= \frac{1}{h} \int_{\mathbb{R}} (gf_X)(x + vh) K^2(v) dv \\ &= \frac{1}{h} \sum_{l=0}^r \frac{h^l}{l!} (gf_X)^{(l)}(x) \int_{\mathbb{R}} v^l K^2(v) dv \\ &\quad + O\left(M_{r+1} h^r \int_{\mathbb{R}} v^{r+1} K^2(v) dv\right) \end{aligned} \quad (\text{B.14})$$

leading to (B.12). □

Denote

$$\mathbf{y} = \{y_i\}_{i=1}^q, \quad \mathbf{F}_{Y|x,t}(\mathbf{y}) = \{F_{Y|x,t}(y_i)\}_{i=1}^q, \quad \widehat{\mathbf{F}}_{Y|x,t}(\mathbf{y}) = \left\{ \widehat{F}_{Y|x,t}(y_i) \right\}_{i=1}^q.$$

The following lemma give the asymptotic properties of $\widehat{\mathbf{F}}_{Y|x,t}(\mathbf{y})$.

Lemma B.3 *Under Assumptions 1 - 3, it holds that*

$$\begin{aligned} \left\{ \frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s} \right\}^{-1/2} \left\{ \widehat{\mathbf{F}}_{Y|x,t}(\mathbf{y}) - \mathbf{F}_{Y|x}(\mathbf{y}) - \mathbf{B}_{F,x}(\mathbf{y}) \sum_{s=1}^t \frac{n_s h_s^2}{N_t} \right\} \\ \xrightarrow{d} N(\mathbf{0}, \boldsymbol{\Sigma}_{F,x}(\mathbf{y})), \end{aligned} \quad (\text{B.15})$$

where

$$\mathbf{B}_{F,x}(\mathbf{y}) = \{B_{F,x}(y_i)\}_{i=1}^q, \quad \Sigma_{F,x}(\mathbf{y}) = [C_{F,x}(y_i, y_j)]_{i,j=1,\dots,q} \quad (\text{B.16})$$

with $B_{F,x}(y_i)$ and $C_{F,x}(y_i, y_j)$ given by (35) and (36), respectively.

Proof For $y \in \mathbb{R}$, denote

$$M_{x,t}(y) = \widehat{S}_{Y|x,t}(y) - F_{Y|x}(y) \widehat{f}_{X,t}(x). \quad (\text{B.17})$$

Then, we have

$$\widehat{F}_{Y|x,t} - F_{Y|x}(y) = \frac{M_{x,t}(y)}{\widehat{f}_{X,t}(x)}. \quad (\text{B.18})$$

Under Assumptions 1 and 2, it follows from Lemma B.2 with $r = 3$ that

$$\begin{aligned} \mathbb{E}[\widehat{S}_{Y|x,t}(y)] &= N_t^{-1} \sum_{s=1}^t \sum_{j=1}^{n_s} \mathbb{E}[\mathbb{E}[I(Y_{sj} < y) | X_{sj}] K_{h_s}(X_{sj} - x)] \\ &= \sum_{s=1}^t \frac{n_s}{N_t} \mathbb{E}[F_{Y|X}(y) K_{h_s}(X - x)] \\ &= F_{Y|x}(y) f_X(x) + \frac{k_{2,1}}{2} \partial_x^2 \{F_{Y|x}(y) f_X(x)\} \sum_{s=1}^t \frac{n_s h_s^2}{N_t} \\ &\quad + O\left(\sum_{s=1}^t \frac{n_s}{N_t} h_s^4\right), \end{aligned} \quad (\text{B.19})$$

$$\begin{aligned} \mathbb{E}[\widehat{f}_{X,t}(x)] &= N_t^{-1} \sum_{s=1}^t \sum_{j=1}^{n_s} \mathbb{E}[K_{h_s}(X_{sj} - x)] \\ &= f_X(x) + \frac{k_{2,1}}{2} f_X^{(2)}(x) \sum_{s=1}^t \frac{n_s h_s^2}{N_t} + O\left(\sum_{s=1}^t \frac{n_s}{N_t} h_s^4\right). \end{aligned} \quad (\text{B.20})$$

Then we have

$$\mathbb{E}[M_{x,t}(y)] - f_X(x) B_{F,x}(y) \sum_{s=1}^t \frac{n_s h_s^2}{N_t} = O\left(\sum_{s=1}^t \frac{n_s}{N_t} h_s^4\right) \quad (\text{B.21})$$

with

$$B_{F,x}(y) = \frac{k_{2,1}}{2} \left\{ \partial_x^2 F_{Y|x}(y) + 2 \partial_x F_{Y|x}(y) f_X'(x) / f_X(x) \right\}. \quad (\text{B.22})$$

Under Assumptions 1, 2 and 3, It is easy to obtain that

$$\text{Var}[\widehat{f}_{X,t}(x)] = \frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t} \text{Var}[K_{h_s}(X_s - x)] = O\left(\frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s}\right) = o(1). \quad (\text{B.23})$$

Combining (B.20) and (B.23), we have

$$\begin{aligned} \widehat{f}_{X,t}(x) &= f_X(x) + \frac{k_{2,1}}{2} f_X^{(2)}(x) \sum_{s=1}^t \frac{n_s h_s^2}{N_t} \\ &\quad + O\left(\sum_{s=1}^t \frac{n_s}{N_t} h_s^4\right) + O_p\left(\sqrt{\frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s}}\right). \end{aligned} \quad (\text{B.24})$$

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For x and $y \in \mathbb{R}$, denote

$$D_{F,x}(y) = I(Y < y) - F_{Y|x}(y). \quad (\text{B.25})$$

For u, y_1 and y_2 in $\mathbb{R}$, we have

$$\begin{aligned} & \mathbb{E} [D_{F,x}(y_1) D_{F,x}(y_2) | X = u] \\ &= \mathbb{E} [I(Y < y_1) I(Y < y_2) | X = u] - \mathbb{E} [I(Y < y_1) | X = u] F_{Y|x}(y_2) \\ & \quad - F_{Y|x}(y_1) \mathbb{E} [I(Y < y_2) | X = u] + F_{Y|x}(y_1) F_{Y|x}(y_2) \\ &= F_{Y|u}(y_1 \wedge y_2) - F_{Y|u}(y_1) F_{Y|x}(y_2) - F_{Y|x}(y_1) F_{Y|u}(y_2) \\ & \quad + F_{Y|x}(y_1) F_{Y|x}(y_2). \end{aligned} \quad (\text{B.26})$$

Noting that the samples are i.i.d., we have

$$\text{Cov}(M_{x,t}(y_1), M_{x,t}(y_2)) = N_t^{-2} \sum_{s=1}^t n_s C_s(y_1, y_2) \quad (\text{B.27})$$

where

$$\begin{aligned} C_s(y_1, y_2) &= \text{Cov}(D_{F,x}(y_1) K_{h_s}(X - x), D_{F,x}(y_2) K_{h_s}(X - x)) \\ &= \mathbb{E} [D_{F,x}(y_1) D_{F,x}(y_2) K_{h_s}^2(X - x)] - \prod_{i=1,2} \mathbb{E} [D_{F,x}(y_i) K_{h_s}(X - x)] \end{aligned} \quad (\text{B.28})$$

with

$$\begin{aligned} & \mathbb{E} [D_{F,x}(y_1) D_{F,x}(y_2) K_{h_s}^2(X - x)] \\ &= \mathbb{E} [\mathbb{E} [D_{F,x}(y_1) D_{F,x}(y_2) | X] K_{h_s}^2(X - x)] \end{aligned} \quad (\text{B.29})$$

$$= \frac{1}{h_s} k_{0,2} \left\{ F_{Y|x}(y_1 \wedge y_2) - F_{Y|x}(y_1) F_{Y|x}(y_2) \right\} f_X(x) + O(h_s),$$

$$\begin{aligned} \mathbb{E} [D_{F,x}(y_i) K_{h_s}(X - x)] &= \mathbb{E} [\mathbb{E} [F_{Y|X}(y_i) - F_{Y|x}(y) | X] K_{h_s}(X - x)] \\ &= O(h^2), \end{aligned} \quad (\text{B.30})$$

where the last equalities in (B.29) and (B.30) are obtained by using Lemma B.2 and (B.26) under the conditions of Assumptions 1 and 2. Inserting (B.29) and (B.30) into (B.28) and further inserting the deduced equation into (B.27), we obtain

$$\begin{aligned} & \text{Cov}(M_{x,t}(y_1), M_{x,t}(y_2)) \\ &= \frac{k_{0,2}}{N_t} \left\{ F_{Y|x}(y_1 \wedge y_2) - F_{Y|x}(y_1) F_{Y|x}(y_2) \right\} f_X(x) \sum_{s=1}^t \frac{n_s}{N_t h_s} \\ & \quad + o \left(\frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s} \right). \end{aligned} \quad (\text{B.31})$$

By Assumption 3, we have

$$\left\{ \frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s} \right\}^{-1/2} \sum_{s=1}^t \frac{n_s}{N_t} h_s^4 \rightarrow 0. \quad (\text{B.32})$$

Combining (B.21), (B.31) and (B.32), and by Lyapunov's central limit theorem, we have

$$\left\{ \frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s} \right\}^{-1/2} \left\{ \{M_{x,t}(y_i)\}_{i=1}^q - f_X(x) \{B_{F,x}(y_i)\}_{i=1}^q \sum_{s=1}^t \frac{n_s h_s^2}{N_t} \right\} \xrightarrow{d} N(0, f_X^2(x) \Sigma_{F,x}(\mathbf{y})). \quad (\text{B.33})$$

By (B.24) and Slutsky's lemma, (B.33) leads to

$$\left\{ \frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s} \right\}^{-1/2} \left\{ \left\{ \frac{M_{x,t}(y_i)}{\hat{f}_{X,t}(x)} \right\}_{i=1}^q - \frac{f_X(x)}{\hat{f}_{X,t}(x)} \{B_{F,x}(y_i)\}_{i=1}^q \sum_{s=1}^t \frac{n_s h_s^2}{N_t} \right\} \xrightarrow{d} N(0, \Sigma_{F,x}(\mathbf{y})). \quad (\text{B.34})$$

Let $x \in I_*$ and from Assumption 1 we know that $f_X(x) > 0$. Then we have

$$\frac{f_X(x)}{\hat{f}_{X,t}(x)} = 1 + O_p \left(\sum_{s=1}^t \frac{n_s h_s^2}{N_t} + \sqrt{\frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s}} \right). \quad (\text{B.35})$$

Combining (B.18), (B.32), (B.34) and (B.35), we obtain (B.15). $\square$

Based on Lemma B.3, we can immediately obtain the asymptotic distribution of $\mathcal{I}_l \hat{F}_{Y|x,t}(y)$ stated in the following two corollaries.

Corollary B.4 *Under Assumptions 1 - 3, it holds that*

$$\left\{ \frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s} \right\}^{-1/2} \left\{ \mathcal{I}_l \hat{F}_{Y|x,t}(y) - \mathcal{I}_l F_{Y|x}(y) - \mathcal{I}_l B_{F,x}(y) \sum_{s=1}^t \frac{n_s h_s^2}{N_t} \right\} \xrightarrow{d} N(\mathbf{0}, \mathcal{I}_l^2 C_{F,x}(y)), \quad (\text{B.36})$$

where

$$\mathcal{I}_l B_{F,x}(y) = \sum_{y_i \in G_x} B_{F,x}(y_i) L(y, y_i; l, G_x), \quad (\text{B.37})$$

$$\mathcal{I}_l^2 C_{F,x}(y) = \sum_{y_i, y_j \in G_x} L(y, y_i; l, G_x) L(y, y_j; l, G_x) C_{F,x}(y_i, y_j). \quad (\text{B.38})$$

Corollary B.5 *Under Assumptions 1 - 3, for any measurable set $I \subset \mathbb{R}$, it holds that*

$$\int_I \left| \mathcal{I}_l \hat{F}_{Y|x,t} - \mathcal{I}_l F_{Y|x} \right|^2 d\mu = \mu(I) O_p \left(\sum_{s=1}^t \frac{n_s h_s^4}{N_t} + \frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s} \right), \quad (\text{B.39})$$

where μ is the Lebesgue measure on $\mathbb{R}$.

Combining Lemma B.1 and Corollary B.4, we obtain Theorem 3.

For any CDF $F : \mathbb{R} \rightarrow \mathbb{R}$ and any measurable function $J_0 : [0, 1] \rightarrow \mathbb{R}$, define the functional Γ by

$$\Gamma(J_0; F) = \int_{\mathbb{R}} (J_0 \circ F) \text{I}_d dF. \quad (\text{B.40})$$

Lemma B.6 *Let F and H be CDFs from $\mathbb{R}$ to $\mathbb{R}$. Assume that F is continuous and strictly increasing on an open set containing $[\underline{\tau}, \bar{\tau}] \subset (0, 1)$, and $J : [0, 1] \rightarrow \mathbb{R}$ is piecewise continuously differentiable with a support in $[\underline{\tau}, \bar{\tau}]$. Then for any $\delta > 0$, it holds that*

$$\Gamma(J; H) = \Gamma(J; F) - \int_{F^{-1}([\underline{\tau}, \bar{\tau}])} (J \circ F)(H - F) d\mu + O\left(\int_{I_F^\delta} (H - F)^2 d\mu\right), \quad (\text{B.41})$$

where $I_F^\delta = (F^{-1}(\underline{\tau}) - \delta, F^{-1}(\bar{\tau}) + \delta)$.

Proof By the formula of integration by parts, we have (see Section 8.1.1 Lemma B in Serfling 1980)

$$\Gamma(J; H) - \Gamma(J; F) = - \int_{\mathbb{R}} (\Phi \circ H - \Phi \circ F) d\mu \quad (\text{B.42})$$

with $\Phi(y) := \int_0^y J(u) du$ for $y \in \mathbb{R}$. Further noting that $(J \circ F)(y) = 0$ for $y \neq F^{-1}([\underline{\tau}, \bar{\tau}])$, we have

$$\Gamma(J; H) - \Gamma(J; F) + \int_{F^{-1}([\underline{\tau}, \bar{\tau}])} (J \circ F)(H - F) d\mu = - \int_{I_{HF}} W_{H,F}(H - F) d\mu, \quad (\text{B.43})$$

where $I_{HF} = F^{-1}([\underline{\tau}, \bar{\tau}]) \cup H^{-1}([\underline{\tau}, \bar{\tau}])$ and

$$W_{H,F}(y) = \begin{cases} \frac{\Phi(H(y)) - \Phi(F(y))}{H(y) - F(y)} - J(F(y)), & \text{if } H(y) \neq F(y), \\ 0, & \text{if } H(y) = F(y). \end{cases} \quad (\text{B.44})$$

Since $J(\cdot)$ is piecewise continuously differentiable with a compact support, then we have

$$M_{J'} := \sup_{\tau \in [0,1] \setminus I_{nc}} |J'(\tau)| < +\infty, \quad (\text{B.45})$$

where $I_{nc} := \{\tau'_1, \dots, \tau'_m\}_{i=1}^m$ the set consists of all the discontinuity points of $J'(\cdot)$. Since F is strictly increasing, we have that the set $I_{F,0} := \{y \in \mathbb{R} : F_{Y|x}(y) \notin \{\tau'_i\}_{i=1}^m, F_{Y|x}(y) \in (\bar{\tau}, \underline{\tau})\}$ is open. Assuming that

$$\int_{I_{HF}} (H - F)^2 d\mu \rightarrow 0, \quad (\text{B.46})$$

then $H \rightarrow F$ on I_{HF} almost everywhere (a.e.) with respect to (w.r.t.) μ , which further implies that

$$\limsup_{H(y) \rightarrow F(y)} \frac{|W_{H,F}(y)(H(y) - F(y))|}{(H(y) - F(y))^2} \leq M_{J'} \quad (\text{B.47})$$

holding a.e. for $y \in I_{F,0} \cap I_{HF}$ w.r.t. μ . Therefore we can deduce

$$\int_{I_{HF}} W_{H,F}(H - F) d\mu = \int_{I_{F,0} \cap I_{HF}} W_{H,F}(H - F) d\mu = O\left(\int_{I_{HF}} (H - F)^2 d\mu\right), \quad (\text{B.48})$$

where the last equality is obtained by combining (B.47) and the Lebesgue's dominated convergence theorem.

Under the assumed conditions on F , there exists $\epsilon > 0$ such that

$$E^\epsilon := \left(F^{-1}(\underline{\tau} - \epsilon) - \epsilon, F^{-1}(\bar{\tau} + \epsilon) + \epsilon \right) \subset \left(F^{-1}(\underline{\tau}) - \delta, F^{-1}(\bar{\tau}) + \delta \right) = I_F^\delta. \quad (\text{B.49})$$

By Markov's inequality, we have

$$\mu \left(\left\{ y \in I_F^\delta : |H(y) - F(y)| \geq \epsilon \right\} \right) \leq \epsilon^{-2} \int_{I_F^\delta} (H - F)^2 d\mu. \quad (\text{B.50})$$

Thus given $\int_{I_F^\delta} (H - F)^2 d\mu \leq \epsilon^3$, we have

$$\mu \left(\left\{ y \in I_F^\delta : |H(y) - F(y)| \geq \epsilon \right\} \right) \leq \epsilon, \quad (\text{B.51})$$

implying $I_{HF} \subset E^\epsilon$ and thus $I_{HF} \subset I_F^\delta$, which further leads to

$$\int_{I_{HF}} (H - F)^2 d\mu = O \left(\int_{I_F^\delta} (H - F)^2 d\mu \right). \quad (\text{B.52})$$

Combining (B.43), (B.48) and (B.52), we obtain (B.41). $\square$

The proof of Theorem 4 is as follows.

Proof of Theorem 4 By the definition in (B.40), we can write

$$\tilde{r}_t(x; J) = \Gamma \left(J; \mathcal{I}_l \hat{F}_{Y|x,t} \right), \quad r(x; J) = \Gamma \left(J; F_{Y|x} \right). \quad (\text{B.53})$$

Then we have the decomposition

$$\tilde{r}_t(x; J) - r(x; J) = \Delta\Gamma + R_{m,x} \quad (\text{B.54})$$

with

$$\Delta\Gamma = \Gamma \left(J; \mathcal{I}_l \hat{F}_{Y|x,t} \right) - \Gamma \left(J; \mathcal{I}_l F_{Y|x} \right), \quad (\text{B.55})$$

$$R_{m,x} = \Gamma \left(J; \mathcal{I}_l F_{Y|x} \right) - \Gamma \left(J; F_{Y|x} \right). \quad (\text{B.56})$$

Under Assumption 4, it follows from Lemma B.6 that

$$\Delta\Gamma = -A_t + O \left(E_{\mathcal{I}_l,t}^2 \right) \quad (\text{B.57})$$

where

$$A_t = \int_{I(G_x)} J \left(F_{Y|x}(y) \right) \left(\mathcal{I}_l \hat{F}_{Y|x,t}(y) - \mathcal{I}_l F_{Y|x}(y) \right) dy, \quad (\text{B.58})$$

$$E_{\mathcal{I}_l,t}^2 = \int_{I(G_x)} \left| \mathcal{I}_l \hat{F}_{Y|x,t}(y) - \mathcal{I}_l F_{Y|x}(y) \right|^2 dy. \quad (\text{B.59})$$

Denoting

$$\omega_i = \int_{I(G_x)} J \left(F_{Y|x}(y) \right) L(y, y_i; l, G_x) dy \quad \text{for } y_i \in G_x,$$

we rewrite (B.58) into

$$A_t = \sum_{y_i \in G_x} \omega_i \left(\hat{F}_{Y|x}(y_i) - F_{Y|x}(y_i) \right). \quad (\text{B.60})$$

By Lemma B.3, we can obtain

$$\left\{ \frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s} \right\}^{-1/2} \left\{ -A_t + \sum_{y_i \in G_x} \omega_i B_{F,x}(y_i) \sum_{s=1}^t \frac{n_s h_s^2}{N_t} \right\} \xrightarrow{d} N \left(0, \sum_{y_i, y_j \in G_x} \omega_i \omega_j C_{F,x}(y_i, y_j) \right). \quad (\text{B.61})$$

By Corollary B.5, we have

$$E_{\mathcal{I}_l, t}^2 = O_p \left(\sum_{s=1}^t \frac{n_s h_s^4}{N_t} + \frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s} \right). \quad (\text{B.62})$$

Further using Assumption 3, we obtain

$$\left\{ \frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s} \right\}^{-1/2} E_{\mathcal{I}_l, t}^2 = o_p(1). \quad (\text{B.63})$$

Combining (B.57), (B.61) and (B.63), we obtain

$$\left\{ \frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s} \right\}^{-1/2} \left\{ \Delta \Gamma - B_{\mathcal{I}_l, m, x} \sum_{s=1}^t \frac{n_s h_s^2}{N_t} \right\} \xrightarrow{d} N(0, \Sigma_{\mathcal{I}_l, m, x}). \quad (\text{B.64})$$

with

$$\begin{aligned} B_{\mathcal{I}_l, m, x} &= - \sum_{y_i \in G_x} \omega_i B_{F,x}(y_i) \\ &= - \int_{I(G_x)} J(F_{Y|x}(y)) \sum_{y_i \in G_x} B_{F,x}(y_i) L(y, y_i; l, G_x) dy \\ &= - \int_{I(G_x)} J(F_{Y|x}(y)) \mathcal{I}_l B_{F,x}(y) dy \\ &= - \int_{I(G_x)} J(F_{Y|x}(y)) B_{F,x}(y) dy + O(|\Delta(G_x)|^{l+1}) \end{aligned} \quad (\text{B.65})$$

and

$$\begin{aligned} \Sigma_{\mathcal{I}_l, m, x} &= \sum_{y_i, y_j \in G_x} \omega_i \omega_j C_{F,x}(y_i, y_j) \\ &= \int_{I(G_x)} \int_{I(G_x)} J(F_{Y|x}(z_1)) J(F_{Y|x}(z_2)) \mathcal{I}_l^2 C_{F,x}(z_1, z_2) dz_1 dz_2. \end{aligned} \quad (\text{B.66})$$

By Lemma B.6, we have

$$R_{\mathcal{I}_l, m, x} = E_1 + E_2, \quad (\text{B.67})$$

where

$$E_1 = \int_{I(G_x)} J(F_{Y|x}(y)) (\mathcal{I}_l F_{Y|x}(y) - F_{Y|x}(y)) dy \quad (\text{B.68})$$

and

$$E_2 = O \left(\int_{[y_1, y_1]} |\mathcal{I}_l F_{Y|x}(y) - F_{Y|x}(y)|^2 dy \right) \quad (\text{B.69})$$

Further using Lemma 1 and Assumption 4, we obtain

$$E_1 = - \int_{I(G_x)} J \left(F_{Y|x} (y) \right) R_{\mathcal{I}_l, F, x} (y) \, \mathrm{d}y, E_2 = O \left(|\Delta(G_x)|^{2l+2} \right). \quad (\text{B.70})$$

Then we have

$$R_{\mathcal{I}_l, m, x} = - \int_{I(G_x)} J \left(F_{Y|x} (y) \right) R_{\mathcal{I}_l, F, x} (y) \, \mathrm{d}y + O \left(|\Delta(G_x)|^{2l+2} \right). \quad (\text{B.71})$$

Combining (B.54), (B.64) and (B.71), we obtain (38). $\square$

The proof of Corollary 5 is as follows.

Proof of Corollary 5 The expansion of $B_{\mathcal{I}_l, m, x}$ can be obtained by using Lemma 1 and Assumption 1. The estimation of $R_{\mathcal{I}_l, m, x}$ is obtained by using the expression of $R_{\mathcal{I}_l, F, x} (y)$ in Theorem 3 and Assumption 1.

Now we deduce the expansion of $\Sigma_{\mathcal{I}_l, F, x}$. By Lemma 1 and Assumption 1, we obtain

$$C_{JF, x} (z_1, z_2) = J \left(F_{Y|x} (z_1) \right) J \left(F_{Y|x} (z_2) \right) C_{F, x} (z_1, z_2) + O \left(|\Delta(G_x)|^{l+1} \right)$$

with $C_{F, x} (z_1, z_2)$ given in (36). Then we express $\Sigma_{\mathcal{I}_l, m, x}$ as

$$\Sigma_{\mathcal{I}_l, m, x} = \Sigma_{m, x} + O \left(|\Delta(G_x)|^{l+1} \right) \quad (\text{B.72})$$

with

$$\Sigma_{m, x} = \int_{I(G_x)} \int_{I(G_x)} J \left(F_{Y|x} (z_1) \right) J \left(F_{Y|x} (z_2) \right) C_{F, x} (z_1, z_2) \, \mathrm{d}z_1 \mathrm{d}z_2.$$

Recalling the expression of $C_{F, x} (z_1, z_2)$ in (36) and using the substitutions $\tau_i = F_{Y|x} (z_i)$ for $i = 1, 2$, we obtain

$$\begin{aligned} \Sigma_{m, x} &= \frac{k_{0,2}}{f_X(x)} \int_{[\underline{\tau}, \bar{\tau}]} \int_{[\underline{\tau}, \bar{\tau}]} \frac{J(\tau_1) J(\tau_2) (\tau_1 \wedge \tau_2 - \tau_1 \tau_2)}{F'_{Y|x} \left(F_{Y|x}^{-1}(\tau_1) \right) F'_{Y|x} \left(F_{Y|x}^{-1}(\tau_2) \right)} \, \mathrm{d}\tau_1 \mathrm{d}\tau_2 \\ &= \frac{k_{0,2} \sigma^2(x)}{f_X(x)} \int_{[\underline{\tau}, \bar{\tau}]} \int_{[\underline{\tau}, \bar{\tau}]} \frac{J(\tau_1) J(\tau_2) (\tau_1 \wedge \tau_2 - \tau_1 \tau_2)}{f_\varepsilon \left(F_\varepsilon^{-1}(\tau_1) \right) f_\varepsilon \left(F_\varepsilon^{-1}(\tau_2) \right)} \, \mathrm{d}\tau_1 \mathrm{d}\tau_2 \\ &= \frac{k_{0,2} \sigma^2(x)}{f_X(x)} \int_{[\underline{\tau}, \bar{\tau}]} \int_{[\underline{\tau}, \bar{\tau}]} S_J(\tau_1, \tau_2) \, \mathrm{d}\tau_1 \mathrm{d}\tau_2, \end{aligned} \quad (\text{B.73})$$

where the integrating range $[\underline{\tau}, \bar{\tau}]$ is obtained by using Assumption 4. Inserting (B.73) into (B.72), we complete the proof. $\square$

The proof of Lemma 7 is as follows.

Proof of Lemma 7 By straightforward calculations, we have

$$\begin{aligned}
\mathcal{E}_t(x; H_t) &= \left(\sum_{s=1}^t \frac{n_s h_s^2}{N_t} \right)^2 (B_{m,x})^2 + \frac{1}{N_t} \sum_{s=1}^t \frac{n_s}{N_t h_s} \Sigma_{m,x} \\
&= N_t^{-2} \left\{ \left(\sum_{s=1}^t n_s h_s^2 \right)^2 (B_{m,x})^2 + \sum_{s=1}^t \frac{n_s}{h_s} \Sigma_{m,x} \right\} \\
&= N_t^{-2} \left\{ \left(\sum_{s=1}^{t-1} n_s h_s^2 + n_t h_t^2 \right)^2 (B_{m,x})^2 + \left(\sum_{s=1}^{t-1} \frac{n_s}{h_s} + \frac{n_t}{h_t} \right) \Sigma_{m,x} \right\}, \\
&= \left(\frac{N_{t-1}}{N_t} \right)^2 N_{t-1}^{-2} \left\{ \left(\sum_{s=1}^{t-1} n_s h_s^2 \right)^2 (B_{m,x})^2 + \sum_{s=1}^{t-1} \frac{n_s}{h_s} \Sigma_{m,x} \right\} \\
&\quad + N_t^{-2} n_t^2 \left\{ h_t^4 (B_{m,x})^2 + \frac{1}{n_t h_t} \Sigma_{m,x} + 2h_t^2 \sum_{s=1}^{t-1} \frac{n_s h_s^2}{n_t} (B_{m,x})^2 \right\}
\end{aligned} \tag{B.74}$$

leading to

$$\mathcal{E}_t(x; H_t) = \left(\frac{N_{t-1}}{N_t} \right)^2 \mathcal{E}_{t-1}(x; H_{t-1}) + \left(\frac{n_t}{N_t} \right)^2 E_t(x, h_t; H_{t-1}), \tag{B.75}$$

where

$$E_t(x, h_t; H_{t-1}) = h_t^4 (B_{m,x})^2 + \frac{1}{n_t h_t} \Sigma_{m,x} + 2h_t^2 \sum_{s=1}^{t-1} \frac{n_s h_s^2}{n_t} (B_{m,x})^2. \tag{B.76}$$

□

The proof of Theorem 8 is as follows.

Proof of Theorem 8 Denote by $\mathbb{L}^2$ the space consists of all the square integrable functions which are defined on $[0, 1]$ and have a support in $[\underline{\tau}, \bar{\tau}]$. Then we have $\mathbb{J}_z(\underline{\tau}, \bar{\tau}) \subset \mathbb{L}^2$. We can express the functional $V : \mathbb{L}^2 \rightarrow \mathbb{R}$ as

$$V(J) = A(J, J) \tag{B.77}$$

with $A : \mathbb{L}^2 \times \mathbb{L}^2 \rightarrow \mathbb{R}$ a bilinear form defined by

$$A(J_1, J_2) = \int_{[\underline{\tau}, \bar{\tau}]^2} J_1(\tau_1) J_2(\tau_2) \frac{\tau_1 \wedge \tau_2 - \tau_1 \tau_2}{f_\varepsilon(F_\varepsilon^{-1}(\tau_1)) f_\varepsilon(F_\varepsilon^{-1}(\tau_2))} d\tau_1 d\tau_2. \tag{B.78}$$

In the following, assume that $J(\cdot)$ minimizes $V(\cdot)$ over $\mathbb{J}_z(\underline{\tau}, \bar{\tau})$. Recalling the constrains in (20), the equality

$$\left. \frac{dV(J + \delta g)}{d\delta} \right|_{\delta=0} = 0 \tag{B.79}$$

holds for any $g(\cdot) \in \mathbb{L}^2$ satisfying

$$\int_{[\underline{\tau}, \bar{\tau}]} g(\tau) d\tau = 0, \quad \int_{[\underline{\tau}, \bar{\tau}]} g(\tau) F_\varepsilon^{-1}(\tau) d\tau = 0. \tag{B.80}$$

By straightforward calculations, we have

$$\begin{aligned} \frac{dV(J + \delta g)}{d\delta} \Big|_{\delta=0} &= A(J, g) = \int_{[\underline{\tau}, \bar{\tau}]^2} J(\tau_1) g(\tau_2) \frac{\tau_1 \wedge \tau_2 - \tau_1 \tau_2}{f_\varepsilon(F_\varepsilon^{-1}(\tau_1)) f_\varepsilon(F_\varepsilon^{-1}(\tau_2))} d\tau_1 d\tau_2 \\ &= \int_{[\underline{\tau}, \bar{\tau}]} \frac{g(\tau_2)}{f_\varepsilon(F_\varepsilon^{-1}(\tau_2))} \left\{ \int_{[\underline{\tau}, \bar{\tau}]} J(\tau_1) \frac{\tau_1 \wedge \tau_2 - \tau_1 \tau_2}{f_\varepsilon(F_\varepsilon^{-1}(\tau_1))} d\tau_1 \right\} d\tau_2 \\ &= 0. \end{aligned} \tag{B.81}$$

Note that $\mathbb{L}^2$ is a Hilbert space, and thus it follows from (B.80) and (B.81) that there exist two constants C_1 and C_2 such that

$$\frac{1}{f_\varepsilon(F_\varepsilon^{-1}(\tau_2))} \left\{ \int_{[\underline{\tau}, \bar{\tau}]} J(\tau_1) \frac{\tau_1 \wedge \tau_2 - \tau_1 \tau_2}{f_\varepsilon(F_\varepsilon^{-1}(\tau_1))} d\tau_1 \right\} = C_1 + C_2 F_\varepsilon^{-1}(\tau_2), \tag{B.82}$$

i.e.,

$$\int_{[\underline{\tau}, \bar{\tau}]} J(\tau_1) \frac{\tau_1 \wedge \tau_2 - \tau_1 \tau_2}{f_\varepsilon(F_\varepsilon^{-1}(\tau_1))} d\tau_1 = \{C_1 + C_2 F_\varepsilon^{-1}(\tau_2)\} f_\varepsilon(F_\varepsilon^{-1}(\tau_2)). \tag{B.83}$$

Taking the operator $\frac{\partial}{\partial \tau_2}$ twice on both sides of (B.83), we deduce

$$\begin{aligned} -\frac{J(\tau_2)}{f_\varepsilon(F_\varepsilon^{-1}(\tau_2))} &= \left(\frac{d}{d\tau_2} \right)^2 \left\{ (C_1 + C_2 F_\varepsilon^{-1}(\tau_2)) f_\varepsilon(F_\varepsilon^{-1}(\tau_2)) \right\} \\ &= C_1 \left(\frac{d}{d\tau_2} \right)^2 f_\varepsilon(F_\varepsilon^{-1}(\tau_2)) + C_2 f_\varepsilon(F_\varepsilon^{-1}(\tau_2)) \left(\frac{d}{d\tau_2} \right)^2 F_\varepsilon^{-1}(\tau_2) \\ &\quad + 2C_2 \frac{d}{d\tau_2} F_\varepsilon^{-1}(\tau_2) \frac{d}{d\tau_2} f_\varepsilon(F_\varepsilon^{-1}(\tau_2)) \\ &\quad + C_2 F_\varepsilon^{-1}(\tau_2) \left(\frac{d}{d\tau_2} \right)^2 f_\varepsilon(F_\varepsilon^{-1}(\tau_2)). \end{aligned} \tag{B.84}$$

By the rules of finding derivative, we have

$$\frac{d}{d\tau} F_\varepsilon^{-1}(\tau) = \left(\frac{1}{f_\varepsilon} \right) (F_\varepsilon^{-1}(\tau)), \quad \frac{d}{d\tau} f_\varepsilon(F_\varepsilon^{-1}(\tau)) = \left(\frac{f'_\varepsilon}{f_\varepsilon} \right) (F_\varepsilon^{-1}(\tau)), \tag{B.85}$$

$$\frac{d}{d\tau} F_\varepsilon^{-1}(\tau) = - \left(\frac{1}{f_\varepsilon^3} \right) (F_\varepsilon^{-1}(\tau)), \tag{B.86}$$

$$\left(\frac{d}{d\tau} \right)^2 f_\varepsilon(F_\varepsilon^{-1}(\tau)) = \left(\frac{f''_\varepsilon f_\varepsilon - (f'_\varepsilon)^2}{f_\varepsilon^3} \right) (F_\varepsilon^{-1}(\tau)) \tag{B.87}$$

Using the equalities in (B.85), (B.86) and (B.87), we can write (B.84) into

$$\begin{aligned} -\frac{J(\tau)}{f_\varepsilon(F_\varepsilon^{-1}(\tau))} &= C_1 \left(\frac{f''_\varepsilon f_\varepsilon - (f'_\varepsilon)^2}{f_\varepsilon^3} \right) (F_\varepsilon^{-1}(\tau)) - C_2 \left(\frac{f'_\varepsilon}{f_\varepsilon^2} \right) (F_\varepsilon^{-1}(\tau)) \\ &\quad + 2C_2 \left(\frac{f'_\varepsilon}{f_\varepsilon^2} \right) (F_\varepsilon^{-1}(\tau)) \\ &\quad + C_2 F_\varepsilon^{-1}(\tau) \left(\frac{f''_\varepsilon f_\varepsilon - (f'_\varepsilon)^2}{f_\varepsilon^3} \right) (F_\varepsilon^{-1}(\tau)), \end{aligned} \tag{B.88}$$

which further leads to

$$\begin{aligned}
 J(\tau) &= - \left(C_1 + C_2 F_\varepsilon^{-1}(\tau) \right) \left(\frac{f_\varepsilon'' f_\varepsilon - (f_\varepsilon')^2}{f_\varepsilon^2} \right) \left(F_\varepsilon^{-1}(\tau) \right) - C_2 \left(\frac{f_\varepsilon'}{f_\varepsilon} \right) \left(F_\varepsilon^{-1}(\tau) \right) \\
 &= - \left(C_1 + C_2 F_\varepsilon^{-1}(\tau) \right) (\log f_\varepsilon)'' \left(F_\varepsilon^{-1}(\tau) \right) - C_2 (\log f_\varepsilon)' \left(F_\varepsilon^{-1}(\tau) \right) \\
 &= - C_1 (\log f_\varepsilon)'' \left(F_\varepsilon^{-1}(\tau) \right) \\
 &\quad - C_2 \left\{ F_\varepsilon^{-1}(\tau) (\log f_\varepsilon)'' \left(F_\varepsilon^{-1}(\tau) \right) + (\log f_\varepsilon)' \left(F_\varepsilon^{-1}(\tau) \right) \right\} \\
 &= C_1 \Psi_1(\tau) + C_2 \Psi_2(\tau)
 \end{aligned} \tag{B.89}$$

with Ψ_1 and Ψ_2 given in (49).

Recalling (20) and (21), the constants (C_1, C_2) should satisfy

$$\begin{aligned}
 C_1 A_{01} + C_2 A_{02} &= 1, & C_1 A_{11} + C_2 A_{12} &= 0, & \text{for } z = m, \\
 C_1 A_{01} + C_2 A_{02} &= 0, & C_1 A_{11} + C_2 A_{12} &= 1, & \text{for } z = \sigma.
 \end{aligned} \tag{B.90}$$

By this we complete the proof. $\square$

The proof of Corollary 9 is as follows.

Proof of Corollary 9 By (49), we have

$$\begin{aligned}
 \Psi_i(\tau) &= - \{ (\delta_{1i} + \delta_{2i} I_d) \log f_\varepsilon \}'' \left(F_\varepsilon^{-1}(\tau) \right) \\
 &= - \{ (\delta_{1i} + \delta_{2i} I_d) (\log f_\varepsilon)'' + 2\delta_{2i} (\log f_\varepsilon)' \} \left(F_\varepsilon^{-1}(\tau) \right)
 \end{aligned} \tag{B.91}$$

By the model (1), we have

$$F_{Y|x}^{-1}(\tau) = m(x) + \sigma(x) F_\varepsilon^{-1}(\tau), \tag{B.92}$$

$$\sigma^l(x) F_{Y|x}^{(l)}(y) = f_\varepsilon^{(l-1)} \left(\frac{y - m(x)}{\sigma(x)} \right) \quad \text{for } l = 1, 2, 3. \tag{B.93}$$

Using the relations in (B.92) and (B.93), we can obtain

$$\begin{aligned}
 (\log f_\varepsilon)' \left(\frac{y - m(x)}{\sigma(x)} \right) &= \frac{f_\varepsilon'}{f_\varepsilon} \left(\frac{y - m(x)}{\sigma(x)} \right) = \sigma(x) \frac{F_{Y|x}''(y)}{F_{Y|x}'(y)} \\
 &= \sigma(x) \left(\log F_{Y|x}' \right)'(y),
 \end{aligned} \tag{B.94}$$

$$\begin{aligned}
 (\log f_\varepsilon)'' \left(\frac{y - m(x)}{\sigma(x)} \right) &= \frac{f_\varepsilon'' f_\varepsilon - (f_\varepsilon')^2}{f_\varepsilon^2} \left(\frac{y - m(x)}{\sigma(x)} \right) \\
 &= \sigma^2(x) \frac{F_{Y|x}^{(3)} F_{Y|x}^{(1)} - (F_{Y|x}^{(2)})^2}{(F_{Y|x}^{(1)})^2}(y) \\
 &= \sigma^2(x) \left(\log F_{Y|x}' \right)''(y).
 \end{aligned} \tag{B.95}$$

Then we can rewrite (B.91) into

$$\begin{aligned}
 \Psi_i \left(F_{Y|x}(y) \right) &= - \left\{ (\delta_{1i} + \delta_{2i} I_d) (\log f_\varepsilon)'' + 2\delta_{2i} (\log f_\varepsilon)' \right\} \left(\frac{y - m(x)}{\sigma(x)} \right) \\
 &= - \left\{ \left(\delta_{1i} + \delta_{2i} \frac{I_d - m(x)}{\sigma(x)} \right) \sigma^2(x) (\log F'_{Y|x})'' + 2\delta_{2i} \sigma(x) (\log F'_{Y|x})' \right\} (y) \\
 &= - \sigma(x) \left\{ (\delta_{1i} \sigma(x) - \delta_{2i} m(x) + \delta_{2i} I_d) \log F'_{Y|x} \right\}'' (y).
 \end{aligned} \tag{B.96}$$

By (B.96), we have

$$\Psi_1 \left(F_{Y|x}(y) \right) = -\sigma^2(x) (\log F'_{Y|x})''(y), \tag{B.97}$$

leading to

$$a_1 \Psi_1(\tau) = - \int_{I_*} (\log F'_{Y|x})'' \left(F_{Y|x}^{-1}(\tau) \right) dx = \tilde{\Psi}_1(\tau) \tag{B.98}$$

with $a_1 = \int_{I_*} \sigma^{-2}(x) dx$. Similarly, it follows from (B.96) that

$$\begin{aligned}
 \Psi_2 \left(F_{Y|x}(y) \right) &= \sigma(x) \left\{ m(x) (\log F'_{Y|x})'' - (I_d \log F'_{Y|x})'' \right\} (y) \\
 &= - \frac{m(x)}{\sigma(x)} \Psi_1 \left(F_{Y|x}(y) \right) - \sigma(x) (I_d \log F'_{Y|x})''(y),
 \end{aligned} \tag{B.99}$$

leading to

$$\frac{1}{\sigma(x)} \Psi_2(\tau) + \frac{m(x)}{\sigma^2(x)} \Psi_1(\tau) = - (I_d \log F'_{Y|x})'' \left(F_{Y|x}^{-1}(\tau) \right), \tag{B.100}$$

which further implies

$$\begin{aligned}
 a_2 \Psi_2(\tau) + a_3 \Psi_1(\tau) &= - \int_{I_*} (I_d \log F'_{Y|x})'' \left(F_{Y|x}^{-1}(\tau) \right) dx \\
 &= \tilde{\Psi}_2(\tau)
 \end{aligned} \tag{B.101}$$

with $a_2 = \int_{I_*} 1/\sigma(x) dx$ and $a_3 = \int_{I_*} m(x)/\sigma^2(x) dx$. Combining (B.98) and (B.101), we conclude that

$$\Psi_1(\tau) = a_1^{-1} \tilde{\Psi}_1(\tau), \quad \Psi_2(\tau) = -a_2^{-1} a_3 \tilde{\Psi}_2(\tau) + a_2^{-1} \tilde{\Psi}_2(\tau), \tag{B.102}$$

i.e., $\{\Psi_1, \Psi_2\}$ can be linearly expressed by $\{\tilde{\Psi}_1, \tilde{\Psi}_2\}$. Then by combining Lemma 2 and Theorem 8, we complete the proof. $\square$

References

Serfling, R.J. 1980. *Approximation theorems of mathematical statistics*. Wiley Series in Probability and Mathematical Statistics. John Wiley & Sons, Inc., New York.