

LOCALLY EFFICIENT ESTIMATORS FOR PARTIALLY LINEAR SINGLE INDEX QUANTILE REGRESSION

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Supplementary Materials

The supplementary materials provide the proofs of Proposition 1, Theorem 1, Theorem 2 and Theorem 3 and additional figures.

S1 Proof of Proposition 1

Proof of Proposition 1: The score function for γ and β_{-1} denoted by $\mathbf{S}_\gamma(y, \mathbf{x}, \mathbf{z})$ and $\mathbf{S}_\beta(y, \mathbf{x}, \mathbf{z})$ is obtained as

$$\mathbf{S}_\gamma(y, \mathbf{x}, \mathbf{z}) = -\frac{f'_\epsilon(\epsilon, \mathbf{x}, \mathbf{z})}{f_\epsilon(\epsilon, \mathbf{x}, \mathbf{z})}\mathbf{x}, \quad \mathbf{S}_\beta(y, \mathbf{x}, \mathbf{z}) = -\frac{f'_\epsilon(\epsilon, \mathbf{x}, \mathbf{z})}{f_\epsilon(\epsilon, \mathbf{x}, \mathbf{z})}g'(\mathbf{z}^\top \boldsymbol{\beta})\mathbf{z}_{-1}.$$

The nuisance tangent space for the three nuisance parameters $f_\epsilon(\epsilon, \mathbf{x}, \mathbf{z})$, $f_{\mathbf{x}, \mathbf{z}}(\mathbf{x}, \mathbf{z})$ and $g(\mathbf{z}^\top \boldsymbol{\beta})$ can be verified to be

$$\begin{aligned} \Lambda &= (\mathbf{f}_1(\epsilon, \mathbf{x}, \mathbf{z}) + \mathbf{f}_2(\mathbf{x}, \mathbf{z}) + \mathbf{f}_3(\mathbf{z}^\top \boldsymbol{\beta})f'_\epsilon(\epsilon, \mathbf{x}, \mathbf{z})/f_\epsilon(\epsilon, \mathbf{x}, \mathbf{z}) : \forall \mathbf{f}_1(\epsilon, \mathbf{x}, \mathbf{z}) \\ &\text{s.t. } E\{\mathbf{f}_1(\epsilon, \mathbf{x}, \mathbf{z})|\mathbf{x}, \mathbf{z}\} = \mathbf{0}, E[\{I(\epsilon < 0) - \tau\}\mathbf{f}_1(\epsilon, \mathbf{x}, \mathbf{z})|\mathbf{x}, \mathbf{z}] = 0, \\ &\forall \mathbf{f}_2(\mathbf{x}, \mathbf{z}) \text{ s.t. } E\{\mathbf{f}_2(\mathbf{x}, \mathbf{z})\} = \mathbf{0}, \forall \mathbf{f}_3(\mathbf{z}^\top \boldsymbol{\beta})), \end{aligned}$$

and the orthogonal complement of Λ is

$$\Lambda^\perp = \left(\frac{f_\epsilon(0, \mathbf{x}, \mathbf{z})}{\tau(1-\tau)} \{I(\epsilon < 0) - \tau\} [\mathbf{a}(\mathbf{x}, \mathbf{z}) - \frac{E\{f_\epsilon^2(0, \mathbf{x}, \mathbf{z})\mathbf{a}(\mathbf{x}, \mathbf{z})|\mathbf{z}^\top\boldsymbol{\beta}\}}{E\{f_\epsilon^2(0, \mathbf{x}, \mathbf{z})|\mathbf{z}^\top\boldsymbol{\beta}\}}] : \forall \mathbf{a}(\mathbf{x}, \mathbf{z}) \right).$$

We now decompose $\mathbf{S}_\beta(\epsilon, \mathbf{x}, \mathbf{z})$ and $\mathbf{S}_\gamma(\epsilon, \mathbf{x}, \mathbf{z})$ as

$$\begin{aligned} \mathbf{S}_\gamma(\epsilon, \mathbf{x}, \mathbf{z}) &= - \left[\frac{f'_\epsilon(\epsilon, \mathbf{x}, \mathbf{z})}{f_\epsilon(\epsilon, \mathbf{x}, \mathbf{z})} - \frac{f_\epsilon(0, \mathbf{x}, \mathbf{z})}{\tau(1-\tau)} \{I(\epsilon < 0) - \tau\} \right] \mathbf{x} \\ &\quad - \frac{f_\epsilon(0, \mathbf{x}, \mathbf{z})}{\tau(1-\tau)} \{I(\epsilon < 0) - \tau\} \frac{E\{f_\epsilon^2(0, \mathbf{x}, \mathbf{z})\mathbf{x}|\mathbf{z}^\top\boldsymbol{\beta}\}}{E\{f_\epsilon^2(0, \mathbf{x}, \mathbf{z})|\mathbf{z}^\top\boldsymbol{\beta}\}} \\ &\quad - \frac{f_\epsilon(0, \mathbf{x}, \mathbf{z})}{\tau(1-\tau)} \{I(\epsilon < 0) - \tau\} \left[\mathbf{x} - \frac{E\{f_\epsilon^2(0, \mathbf{x}, \mathbf{z})\mathbf{x}|\mathbf{z}^\top\boldsymbol{\beta}\}}{E\{f_\epsilon^2(0, \mathbf{x}, \mathbf{z})|\mathbf{z}^\top\boldsymbol{\beta}\}} \right], \\ \mathbf{S}_\beta(\epsilon, \mathbf{x}, \mathbf{z}) &= - \left[\frac{f'_\epsilon(\epsilon, \mathbf{x}, \mathbf{z})}{f_\epsilon(\epsilon, \mathbf{x}, \mathbf{z})} - \frac{f_\epsilon(0, \mathbf{x}, \mathbf{z})}{\tau(1-\tau)} \{I(\epsilon < 0) - \tau\} \right] g'(\mathbf{z}^\top\boldsymbol{\beta})\mathbf{z}_{-1} \\ &\quad - \frac{f_\epsilon(0, \mathbf{x}, \mathbf{z})}{\tau(1-\tau)} \{I(\epsilon < 0) - \tau\} g'(\mathbf{z}^\top\boldsymbol{\beta}) \frac{E\{f_\epsilon^2(0, \mathbf{x}, \mathbf{z})\mathbf{z}_{-1}|\mathbf{z}^\top\boldsymbol{\beta}\}}{E\{f_\epsilon^2(0, \mathbf{x}, \mathbf{z})|\mathbf{z}^\top\boldsymbol{\beta}\}} \\ &\quad - \frac{f_\epsilon(0, \mathbf{x}, \mathbf{z})}{\tau(1-\tau)} \{I(\epsilon < 0) - \tau\} g'(\mathbf{z}^\top\boldsymbol{\beta}) \left[\mathbf{z}_{-1} - \frac{E\{f_\epsilon^2(0, \mathbf{x}, \mathbf{z})\mathbf{z}_{-1}|\mathbf{z}^\top\boldsymbol{\beta}\}}{E\{f_\epsilon^2(0, \mathbf{x}, \mathbf{z})|\mathbf{z}^\top\boldsymbol{\beta}\}} \right]. \end{aligned}$$

It is easily verified that the first two terms of $\{\mathbf{S}_\gamma^\top(\epsilon, \mathbf{x}, \mathbf{z}), \mathbf{S}_\beta^\top(\epsilon, \mathbf{x}, \mathbf{z})\}^\top$ are elements in the nuisance tangent space Λ , while the last term belongs to the orthogonal complement $\Lambda^\perp$. Hence the efficient score function which is the projection of the score function is the last component.

S2 Notations

To ease the description, we first introduce several notations. Define

$$\begin{aligned} \mathbf{x}_i^c &\equiv \mathbf{x}_i - \frac{E\{f_\epsilon^{*2}(0, \mathbf{x}_i, \mathbf{z}_i)\mathbf{x}_i|\mathbf{z}_i^\top\boldsymbol{\beta}\}}{E\{f_\epsilon^{*2}(0, \mathbf{x}_i, \mathbf{z}_i)|\mathbf{z}_i^\top\boldsymbol{\beta}\}}, \\ \mathbf{z}_{-1,i}^c &\equiv \mathbf{z}_{-1,i} - \frac{E\{f_\epsilon^{*2}(0, \mathbf{x}_i, \mathbf{z}_i)\mathbf{z}_{-1,i}|\mathbf{z}_i^\top\boldsymbol{\beta}\}}{E\{f_\epsilon^{*2}(0, \mathbf{x}_i, \mathbf{z}_i)|\mathbf{z}_i^\top\boldsymbol{\beta}\}}, \end{aligned}$$

$$\begin{aligned}
P(\mathbf{x}_i, \mathbf{z}_i) &\equiv \{(\mathbf{x}_i^c)^T, g'(\mathbf{z}_i^T \boldsymbol{\beta})(\mathbf{z}_{-1,i}^c)^T\}^T, \\
\hat{P}(\mathbf{x}_i, \mathbf{z}_i) &\equiv \{(\hat{\mathbf{x}}_i^c)^T, \tilde{g}'(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma})(\hat{\mathbf{z}}_{-1,i}^c)^T\}^T, \\
\alpha &\equiv \sup_{\mathbf{x}, \mathbf{z}} \|P(\mathbf{x}, \mathbf{z})\|, \\
V_0 &\equiv E \left\{ \frac{f_\epsilon^{*2}(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau)} \begin{pmatrix} \mathbf{x}_i^c \\ g'(\mathbf{z}_i^T \boldsymbol{\beta}) \mathbf{z}_{-1,i}^c \end{pmatrix} \begin{pmatrix} \mathbf{x}_i^T & g'(\mathbf{z}_i^T \boldsymbol{\beta}) \mathbf{z}_{-1,i}^T \end{pmatrix} \right\}, \\
&G_i\{\tilde{\gamma}, \tilde{\boldsymbol{\beta}}, \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma})\} \\
&\equiv \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau)} [\tau - I\{Y_i - \mathbf{x}_i^T \tilde{\gamma} - \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}) < 0\}] P(\mathbf{x}_i, \mathbf{z}_i), \\
&G_i\{\gamma, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta})\} \\
&\equiv \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau)} [\tau - I\{Y_i - \mathbf{x}_i^T \gamma - g(\mathbf{z}_i^T \boldsymbol{\beta}) < 0\}] P(\mathbf{x}_i, \mathbf{z}_i), \\
&G_{pi}\{\tilde{\gamma}, \tilde{\boldsymbol{\beta}}, \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma})\} \\
&\equiv \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau)} (\tau - F_\epsilon[\{\mathbf{x}_i^T (\tilde{\gamma} - \gamma) + \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}) - g(\mathbf{z}_i^T \boldsymbol{\beta})\}, \mathbf{x}_i, \mathbf{z}_i]) P(\mathbf{x}_i, \mathbf{z}_i), \\
&\tilde{G}_{pi}\{\tilde{\gamma}, \tilde{\boldsymbol{\beta}}, \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma})\} \\
&\equiv \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)}{-\tau(1-\tau)} \{\mathbf{x}_i^T (\tilde{\gamma} - \gamma) + \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}) - g(\mathbf{z}_i^T \boldsymbol{\beta})\} P(\mathbf{x}_i, \mathbf{z}_i).
\end{aligned}$$

Finally, let

$$\begin{aligned}
&\eta_{mi}\{\gamma, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta}), \gamma^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \gamma^*)\} \\
&\equiv G_i\{\gamma^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \gamma^*)\} - G_i\{\gamma, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta})\} - G_{pi}\{\gamma^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \gamma^*)\},
\end{aligned}$$

and $\mathcal{D} \equiv \{(\boldsymbol{\beta}^{*T}, \gamma^{*T})^T : \|\boldsymbol{\beta}^* - \boldsymbol{\beta}\| \leq Cn^{-1/2}, \|\gamma^* - \gamma\| \leq Cn^{-1/2}, \boldsymbol{\beta}_1^* = 1\}$. Note that here, $E[G_i\{\gamma, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta})\} | \mathbf{x}_i, \mathbf{z}_i] = 0$. With the dependence of the estimates on the data ignored, $G_{pi}\{\tilde{\gamma}, \tilde{\boldsymbol{\beta}}, \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma})\}$ can be viewed as the expectation of $G_i\{\tilde{\gamma}, \tilde{\boldsymbol{\beta}}, \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma})\}$ given $\mathbf{x}_i$ and $\mathbf{z}_i$. Further, $\tilde{G}_{pi}\{\tilde{\gamma}, \tilde{\boldsymbol{\beta}}, \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma})\}$ is the first order approximation of $G_{pi}\{\tilde{\gamma}, \tilde{\boldsymbol{\beta}}, \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma})\}$.

Define

$$\begin{aligned}
 \mathbf{x}_i^{c0} &\equiv \mathbf{x}_i - \frac{E\{f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)\mathbf{x}_i | \mathbf{z}_i^T \boldsymbol{\beta}\}}{E\{f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i) | \mathbf{z}_i^T \boldsymbol{\beta}\}}, \\
 \mathbf{z}_{-1,i}^{c0} &\equiv \mathbf{z}_{-1,i} - \frac{E\{f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)\mathbf{z}_{-1,i} | \mathbf{z}_i^T \boldsymbol{\beta}\}}{E\{f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i) | \mathbf{z}_i^T \boldsymbol{\beta}\}}, \\
 P^0(\mathbf{x}_i, \mathbf{z}_i) &\equiv \{(\mathbf{x}_i^{c0})^T, g'(\mathbf{z}_i^T \boldsymbol{\beta})(\mathbf{z}_{-1,i}^{c0})^T\}^T, \\
 V &\equiv E \left\{ \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i)f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau)} P(\mathbf{x}_i, \mathbf{z}_i) P^0(\mathbf{x}_i, \mathbf{z}_i)^T \right\}.
 \end{aligned}$$

S3 Proof of Theorem 1

Define

$$\tilde{F}_p(\phi, \boldsymbol{\gamma}, \boldsymbol{\beta}) \equiv \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) \text{pr}\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma} - \phi < 0 | \mathbf{z}_j^T \boldsymbol{\beta}\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})}.$$

We first introduce a new notation $\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta})$, which is defined as the solution of ϕ that solves $\tilde{F}_p(\phi, \boldsymbol{\gamma}, \boldsymbol{\beta}) = \tau$. Thus, we always have $\tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}, \boldsymbol{\beta}\} = \tau$. We first prove two lemmas.

Lemma 1. Under the Regularity Conditions C2-C5, $\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_i^T \boldsymbol{\beta}) = O_p\{k(n, h_1)\}$.

Proof. We aim to show that there exists a constant $C > 0$ such that $\text{pr}\{g(\mathbf{z}_i^T \boldsymbol{\beta}) - Ck(n, h_1) \leq \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) \leq g(\mathbf{z}_i^T \boldsymbol{\beta}) + Ck(n, h_1)\} \rightarrow 1$ as $n \rightarrow \infty$. It is equivalent to prove that, for arbitrary $C_1 > C > 0$, $\text{pr}\{|\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_i^T \boldsymbol{\beta})| > C_1 k(n, h_1)\} \rightarrow 0$ as $n \rightarrow \infty$. We prove this by contradiction. If $|\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_i^T \boldsymbol{\beta})| > C_1 k(n, h_1)$, then $\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) > g(\mathbf{z}_i^T \boldsymbol{\beta}) + C_1 k(n, h_1)$ or $\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) < g(\mathbf{z}_i^T \boldsymbol{\beta}) - C_1 k(n, h_1)$, then by the monotonicity of the conditional distribution function, we have

$$\text{pr}\{Y_i - \mathbf{x}_i^T \boldsymbol{\gamma} < \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}\} \geq \text{pr}\{\epsilon_i < C_1 k(n, h_1) | \mathbf{z}_i^T \boldsymbol{\beta}\}, \quad (\text{S3.1})$$

or

$$\Pr\{Y_i - \mathbf{x}_i^T \boldsymbol{\gamma} < \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}\} \leq \Pr\{\epsilon_i < -C_1 k(n, h_1) | \mathbf{z}_i^T \boldsymbol{\beta}\}. \quad (\text{S3.2})$$

For any C_1 , under Conditions C2, C4 and C5, standard kernel regression analysis leads to

$$\begin{aligned} \tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}, \boldsymbol{\beta}\} &= \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) \Pr\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma} < \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) | \mathbf{z}_j^T \boldsymbol{\beta}\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})} \\ &= \Pr\{Y_i - \mathbf{x}_i^T \boldsymbol{\gamma} < \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}\} + O_p\{k(n, h_1)\}. \end{aligned}$$

Thus, for any $\delta > 0$, there exists a constant $C_2 > 0$, so that with probability at least $1 - \delta$,

$$\Pr\{Y_i - \mathbf{x}_i^T \boldsymbol{\gamma} < \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}\} \leq \tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}, \boldsymbol{\beta}\} + C_2 k(n, h_1),$$

and

$$\tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}, \boldsymbol{\beta}\} - C_2 k(n, h_1) \leq \Pr\{Y_i - \mathbf{x}_i^T \boldsymbol{\gamma} < \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}\}.$$

Note that $\tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}, \boldsymbol{\beta}\} = \tau$ and $\Pr(\epsilon_i < 0 | \mathbf{z}_i^T \boldsymbol{\beta}) = \tau$. Then the above equations become

$$\Pr\{Y_i - \mathbf{x}_i^T \boldsymbol{\gamma} < \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}\} \leq \Pr(\epsilon_i < 0 | \mathbf{z}_i^T \boldsymbol{\beta}) + C_2 k(n, h_1), \quad (\text{S3.3})$$

and

$$\Pr(\epsilon_i < 0 | \mathbf{z}_i^T \boldsymbol{\beta}) - C_2 k(n, h_1) \leq \Pr\{Y_i - \mathbf{x}_i^T \boldsymbol{\gamma} < \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}\}. \quad (\text{S3.4})$$

Combining (S3.1), (S3.2), (S3.3) and (S3.4), we get

$$\Pr\{\epsilon_i < C_1 k(n, h_1) | \mathbf{z}_i^T \boldsymbol{\beta}\} - \Pr(\epsilon_i < 0 | \mathbf{z}_i^T \boldsymbol{\beta}) \leq C_2 k(n, h_1),$$

or

$$-C_2 k(n, h_1) \leq \Pr\{\epsilon_i < -C_1 k(n, h_1) | \mathbf{z}_i^T \boldsymbol{\beta}\} - \Pr(\epsilon_i < 0 | \mathbf{z}_i^T \boldsymbol{\beta}).$$

But by a first-order Taylor series expansion and Condition C2,

$$\Pr(\epsilon_i < 0 | \mathbf{z}_i^T \boldsymbol{\beta}) + f_{\epsilon | \mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) C_1 k(n, h_1) / 2 \leq \Pr\{\epsilon_i < C_1 k(n, h_1) | \mathbf{z}_i^T \boldsymbol{\beta}\},$$

and

$$\Pr\{\epsilon_i < -C_1 k(n, h_1) | \mathbf{z}_i^T \boldsymbol{\beta}\} \leq \Pr(\epsilon_i < 0 | \mathbf{z}_i^T \boldsymbol{\beta}) - f_{\epsilon | \mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) C_1 k(n, h_1) / 2.$$

This leads to $f_{\epsilon | \mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) C_1 k(n, h_1) / 2 \leq C_2 k(n, h_1)$, which is impossible to hold for a fixed C_2 and arbitrary $C_1 > C > 0$ under Condition C2. Thus,

$$\begin{aligned} \Pr\{|\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_i^T \boldsymbol{\beta})| > C_1 k(n, h_1)\} &\leq \Pr\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) > g(\mathbf{z}_i^T \boldsymbol{\beta}) + C_1 k(n, h_1)\} \\ &\quad + \Pr\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) < g(\mathbf{z}_i^T \boldsymbol{\beta}) - C_1 k(n, h_1)\} \rightarrow 0. \end{aligned}$$

Lemma 1 is proved.

Lemma 2. Under the Regularity Conditions C1-C8, $\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}) - \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) = O_p\{k(n, h_1)\}$.

Proof. Recall that

$$\tilde{F}(\phi, \tilde{\gamma}, \tilde{\beta}) \equiv \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\beta} - \mathbf{z}_i^T \tilde{\beta}) I(Y_j - \mathbf{x}_j^T \tilde{\gamma} - \phi < 0)}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\beta} - \mathbf{z}_i^T \tilde{\beta})}.$$

Note that $\tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\beta}\} = \tau$.

We aim to show that there exists a constant $C > 0$ such that $\text{pr}\{\tilde{g}_p(\mathbf{z}_i^T \beta) - Ck(n, h_1) \leq \tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}) \leq \tilde{g}_p(\mathbf{z}_i^T \beta) + Ck(n, h_1)\} \rightarrow 1$ as $n \rightarrow \infty$. It is equivalent to prove that, for arbitrary $C_1 > C > 0$, $\text{pr}\{|\tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}) - \tilde{g}_p(\mathbf{z}_i^T \beta)| > C_1 k(n, h_1)\} \rightarrow 0$ as $n \rightarrow \infty$. We prove this by contradiction. If $|\tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}) - \tilde{g}_p(\mathbf{z}_i^T \beta)| > C_1 k(n, h_1)$, then either $\tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}) > \tilde{g}_p(\mathbf{z}_i^T \beta) + C_1 k(n, h_1)$ or $\tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}) < \tilde{g}_p(\mathbf{z}_i^T \beta) - C_1 k(n, h_1)$.

Consider first the case when $\tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}) < \tilde{g}_p(\mathbf{z}_i^T \beta) - C_1 k(n, h_1)$. By the monotonicity of the conditional distribution function, we have

$$\begin{aligned} & \text{pr}\{Y_i - \mathbf{x}_i^T \gamma < \tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}) | \mathbf{z}_i^T \beta\} \\ & \leq \text{pr}\{Y_i - \mathbf{x}_i^T \gamma < \tilde{g}_p(\mathbf{z}_i^T \beta) - C_1 k(n, h_1) | \mathbf{z}_i^T \beta\}. \end{aligned} \quad (\text{S3.5})$$

Under Conditions C2, C4 and C5, standard kernel regression analysis leads to

$$\begin{aligned} \tilde{F}_p\{\tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}), \gamma, \beta\} &= \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \beta - \mathbf{z}_i^T \beta) \text{pr}\{Y_j - \mathbf{x}_j^T \gamma < \tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}) | \mathbf{z}_j^T \beta\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \beta - \mathbf{z}_i^T \beta)} \\ &= \text{pr}\{Y_i - \mathbf{x}_i^T \gamma < \tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}) | \mathbf{z}_i^T \beta\} + O_p\{k(n, h_1)\}. \end{aligned}$$

$$\begin{aligned} & \tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \beta) - C_1 k(n, h_1), \gamma, \beta\} \\ &= \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \beta - \mathbf{z}_i^T \beta) \text{pr}\{Y_j - \mathbf{x}_j^T \gamma < \tilde{g}_p(\mathbf{z}_i^T \beta) - C_1 k(n, h_1) | \mathbf{z}_j^T \beta\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \beta - \mathbf{z}_i^T \beta)} \\ &= \text{pr}\{Y_i - \mathbf{x}_i^T \gamma < \tilde{g}_p(\mathbf{z}_i^T \beta) - C_1 k(n, h_1) | \mathbf{z}_i^T \beta\} + O_p\{k(n, h_1)\}. \end{aligned}$$

Thus, for any $\delta > 0$, there exists a constant $C_2 > 0$, so that with probability at least $1 - \delta$,

$$\tilde{F}_p\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \gamma, \boldsymbol{\beta}\} - C_2 k(n, h_1) \leq \text{pr}\{Y_i - \mathbf{x}_i^T \gamma < \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}) | \mathbf{z}_i^T \boldsymbol{\beta}\}, \quad (\text{S3.6})$$

$$\begin{aligned} & \text{pr}\{Y_i - \mathbf{x}_i^T \gamma < \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - C_1 k(n, h_1) | \mathbf{z}_i^T \boldsymbol{\beta}\} \\ & \leq \tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - C_1 k(n, h_1), \gamma, \boldsymbol{\beta}\} + C_2 k(n, h_1). \end{aligned} \quad (\text{S3.7})$$

Combining (S3.5), (S3.6) and (S3.7), we get

$$\tilde{F}_p\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \gamma, \boldsymbol{\beta}\} \leq \tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - C_1 k(n, h_1), \gamma, \boldsymbol{\beta}\} + 2C_2 k(n, h_1). \quad (\text{S3.8})$$

By direct calculation, we get

$$\begin{aligned} & \tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} - \tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \boldsymbol{\beta}\} \\ = & \frac{\sum_{j \in I_1} \{K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) - K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})\} I\{Y_j - \mathbf{x}_j^T \tilde{\gamma} < \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma})\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})} \\ & + \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) I\{Y_j - \mathbf{x}_j^T \tilde{\gamma} < \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma})\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})} \\ & \times \frac{\sum_{j \in I_1} \{K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) - K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})}. \end{aligned} \quad (\text{S3.9})$$

For notational brevity, let

$$\xi_j(\mathbf{z}_i, \boldsymbol{\beta}) \equiv K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) I\{Y_j - \mathbf{x}_j^T \tilde{\gamma} < \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma})\}, j \in I_1.$$

Under Conditions C1, C5, and C6, for all $\mathbf{z}_i$ and $\|\boldsymbol{\beta}^* - \boldsymbol{\beta}\| = O_p(n^{-1/2})$,

$$E\{\xi_j(\mathbf{z}_i, \boldsymbol{\beta}^*) - \xi_j(\mathbf{z}_i, \boldsymbol{\beta})\}^2 = O_p(n^{-1}h_1^{-4}). \quad (\text{S3.10})$$

By Chebyshev's inequality, we can get

$$\text{pr}(|\xi_j(\mathbf{z}_i, \boldsymbol{\beta}^*) - \xi_j(\mathbf{z}_i, \boldsymbol{\beta})| \geq 1) \leq E\{\xi_j(\mathbf{z}_i, \boldsymbol{\beta}^*) - \xi_j(\mathbf{z}_i, \boldsymbol{\beta})\}^2. \quad (\text{S3.11})$$

Let $\zeta(\mathbf{z}_i, \boldsymbol{\beta}^*, \boldsymbol{\beta}) = 1/n \sum_{j \in I_1} \{\xi_j(\mathbf{z}_i, \boldsymbol{\beta}^*) - \xi_j(\mathbf{z}_i, \boldsymbol{\beta})\}$. Under Condition C4, (S3.10) and (S3.11), together with Lemma 18 (page 20), Lemma 25 (page 27), Lemma 28 (page 30), the proof of Lemma 33 (page 31-33) and Theorem 37 (page 34) in Pollard (1984), yield

$$\sup_{\|\boldsymbol{\beta}^* - \boldsymbol{\beta}\| = O_p(n^{-1/2})} \sup_{\mathbf{z}_i} |\zeta(\mathbf{z}_i, \boldsymbol{\beta}^*, \boldsymbol{\beta}) - E\zeta(\mathbf{z}_i, \boldsymbol{\beta}^*, \boldsymbol{\beta})| = O_p(n^{-1}h_1^{-2}\log n) = o_p(n^{-1/2}) \quad (\text{S3.12})$$

under Condition C4. By direct derivation, at fixed $\mathbf{z}_i$, for any $\boldsymbol{\beta}^*$ satisfying $\|\boldsymbol{\beta}^* - \boldsymbol{\beta}\| = O_p(n^{-1/2})$, we have

$$E\{\xi_j(\mathbf{z}_i, \boldsymbol{\beta}^*)\} = \int K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta}^* - \mathbf{z}_i^T \boldsymbol{\beta}^*) w(\mathbf{z}_j^T \boldsymbol{\beta}^*) d\mathbf{z}_j^T \boldsymbol{\beta}^* = w(\mathbf{z}_i^T \boldsymbol{\beta}^*) + O_p(h_1^4). \quad (\text{S3.13})$$

where $w(\mathbf{z}_j^T \boldsymbol{\beta}^*) \equiv \text{pr}\{Y_j - \mathbf{x}_j^T \tilde{\boldsymbol{\gamma}} < \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\boldsymbol{\gamma}}) | \mathbf{z}_i, \mathbf{z}_j^T \boldsymbol{\beta}^*\} f_{\mathbf{z}^T \boldsymbol{\beta}^*}(\mathbf{z}_j^T \boldsymbol{\beta}^*)$. Similarly, it can be shown that $E\xi_j(\mathbf{z}_i, \boldsymbol{\beta}) = w(\mathbf{z}_i^T \boldsymbol{\beta}) + O_p(h_1^4)$. Then under Conditions C7 and C8, we have $|E\zeta(\mathbf{z}_i, \boldsymbol{\beta}^*, \boldsymbol{\beta})| = |E\{\xi_j(\mathbf{z}_i, \boldsymbol{\beta}^*) - \xi_j(\mathbf{z}_i, \boldsymbol{\beta})\}| = |w(\mathbf{z}_i^T \boldsymbol{\beta}^*) - w(\mathbf{z}_i^T \boldsymbol{\beta})| + O_p(h_1^4)$. This means

$$\sup_{\|\boldsymbol{\beta}^* - \boldsymbol{\beta}\| = O_p(n^{-1/2})} \sup_{\mathbf{z}_i} |E\zeta(\mathbf{z}_i, \boldsymbol{\beta}^*, \boldsymbol{\beta})| = O_p(n^{-1/2} + h_1^4). \quad (\text{S3.14})$$

Under Condition C4, combining (S3.12) and (S3.14), it is obtained that the first term in

(S3.9) is $O_p(n^{-1/2})$. Similarly, we can prove the second term in (S3.9) is $O_p(n^{-1/2})$. Then we have

$$\tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} - \tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \boldsymbol{\beta}\} = O_p(n^{-1/2}). \quad (\text{S3.15})$$

Under Conditions C2, C4 and C5, standard kernel regression analysis leads to

$$\tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \boldsymbol{\beta}\} - \tilde{F}_p\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \boldsymbol{\beta}\} = O_p\{k(n, h_1)\}. \quad (\text{S3.16})$$

Under Conditions C1 and C3, we also have

$$\tilde{F}_p\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \boldsymbol{\beta}\} - \tilde{F}_p\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \gamma, \boldsymbol{\beta}\} = O_p(n^{-1/2}). \quad (\text{S3.17})$$

Combining (S3.15), (S3.16) and (S3.17), we get

$$\tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} - \tilde{F}_p\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \gamma, \boldsymbol{\beta}\} = O_p\{k(n, h_1)\}.$$

Thus, for any $\delta > 0$, there exists a constant $C_3 > 0$, so that with probability at least $1 - \delta$,

$$\tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} - C_3 k(n, h_1) \leq \tilde{F}_p\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \gamma, \boldsymbol{\beta}\}. \quad (\text{S3.18})$$

Combining (S3.8) and (S3.18), we get

$$\tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} - C_3 k(n, h_1) \leq \tilde{F}_p\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \gamma, \boldsymbol{\beta}\} - C_1 k(n, h_1) + 2C_2 k(n, h_1).$$

That is

$$\tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} \leq \tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - C_1 k(n, h_1), \gamma, \boldsymbol{\beta}\} + C_4 k(n, h_1),$$

where $C_4 = 2C_2 + C_3$. Note that $\tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} = \tau$ and $\tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}), \gamma, \boldsymbol{\beta}\} = \tau$.

Combining this and the above equation, we get

$$\tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}), \gamma, \boldsymbol{\beta}\} \leq \tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - C_1 k(n, h_1), \gamma, \boldsymbol{\beta}\} + C_4 k(n, h_1). \quad (\text{S3.19})$$

By a first-order Taylor series expansion, we get

$$\begin{aligned} & \tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - C_1 k(n, h_1), \gamma, \boldsymbol{\beta}\} \\ &= \tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}), \gamma, \boldsymbol{\beta}\} - \tilde{F}'_p\{\tilde{g}^*(\mathbf{z}_i^T \boldsymbol{\beta}), \gamma, \boldsymbol{\beta}\} C_1 k(n, h_1), \end{aligned} \quad (\text{S3.20})$$

where

$$\tilde{F}'_p\{\tilde{g}^*(\mathbf{z}_i^T \boldsymbol{\beta}), \gamma, \boldsymbol{\beta}\} = \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}\{\tilde{g}^*(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_j^T \boldsymbol{\beta}\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})},$$

and $\tilde{g}^*(\mathbf{z}_i^T \boldsymbol{\beta})$ is between $\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - C_1 k(n, h_1)$ and $\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta})$. Combining (S3.20), using Lemma

1 and standard kernel regression analysis, we get

$$\begin{aligned} & \tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - C_1 k(n, h_1), \gamma, \boldsymbol{\beta}\} \\ &= \tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}), \gamma, \boldsymbol{\beta}\} - f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0 | \mathbf{z}_i^T \boldsymbol{\beta}) C_1 k(n, h_1) + O_p\{k(n, h_1)\}. \end{aligned} \quad (\text{S3.21})$$

So for any $\delta > 0$, there exists a constant $C_5 > 0$, so that with probability at least $1 - \delta$,

under Condition C2,

$$\begin{aligned} & \tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - C_1 k(n, h_1), \boldsymbol{\gamma}, \boldsymbol{\beta}\} \\ & \leq \tilde{F}_p\{\tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}, \boldsymbol{\beta}\} - 1/2 f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0|\mathbf{z}_i^T \boldsymbol{\beta}) C_1 k(n, h_1) + C_5 k(n, h_1). \end{aligned} \quad (\text{S3.22})$$

(S3.19) and (S3.22) lead to $1/2 f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0|\mathbf{z}_i^T \boldsymbol{\beta}) C_1 k(n, h_1) \leq (C_4 + C_5) k(n, h_1)$, which is impossible to hold for fixed constants C_4 and C_5 and arbitrary $C_1 > C > 0$ under Condition C2.

This means

$$\text{pr}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\boldsymbol{\gamma}}) < \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) - C_1 k(n, h_1)\} \rightarrow 0.$$

Similarly we can consider the case $\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\boldsymbol{\gamma}}) > \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) + C_1 k(n, h_1)$ and prove $\text{pr}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\boldsymbol{\gamma}}) > \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta}) + C_1 k(n, h_1)\} \rightarrow 0$. Thus, for arbitrary $C_1 > C > 0$, $\text{pr}\{|\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\boldsymbol{\gamma}}) - \tilde{g}_p(\mathbf{z}_i^T \boldsymbol{\beta})| > C_1 k(n, h_1)\} \rightarrow 0$ as $n \rightarrow \infty$. Lemma 2 is proved.

Proof of Theorem 1. Combining the results in Lemmas 1 and 2, Theorem 1 is shown.

S4 Proof of Theorem 2

We first define some notations used in the proof of Theorem 2. Let $a_n \equiv k(n, h_1) \log n$. For any possibly random $\boldsymbol{\beta}^*$ and $\boldsymbol{\gamma}^*$ satisfying $\|\boldsymbol{\beta}^* - \boldsymbol{\beta}\| \leq C n^{-1/2}$, $\|\boldsymbol{\gamma}^* - \boldsymbol{\gamma}\| \leq C n^{-1/2}$, let

$$\begin{aligned} T_n(\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) & \equiv \tilde{U}(\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \tilde{U}\{g(\mathbf{z}_i^T \boldsymbol{\beta}^*), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\} \\ & \quad - [\tilde{U}_p(\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \tilde{U}_p\{g(\mathbf{z}_i^T \boldsymbol{\beta}^*), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\}], \\ T_n^-(\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) & \equiv \tilde{U}^-(\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \tilde{U}^-\{g(\mathbf{z}_i^T \boldsymbol{\beta}^*), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\} \\ & \quad - [\tilde{U}_p^-(\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \tilde{U}_p^-\{g(\mathbf{z}_i^T \boldsymbol{\beta}^*), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\}], \end{aligned}$$

$$\begin{aligned}
\tilde{U}(\eta, \gamma^*, \beta^*) &\equiv \frac{1}{n} \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*) I(Y_j - \mathbf{x}_j^T \gamma^* - \eta < 0), \\
\tilde{U}_p(\eta, \gamma^*, \beta^*) &\equiv \frac{1}{n} \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*) \text{pr}(Y_j - \mathbf{x}_j^T \gamma^* - \eta < 0 | \mathbf{z}_j^T \beta^*), \\
\tilde{U}^+(\eta, \gamma^*, \beta^*) &\equiv \frac{1}{n} \sum_{j \in I_1} K_{h_1}^+(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*) I(Y_j - \mathbf{x}_j^T \gamma^* - \eta < 0), \\
\tilde{U}^-(\eta, \gamma^*, \beta^*) &\equiv \frac{1}{n} \sum_{j \in I_1} K_{h_1}^-(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*) I(Y_j - \mathbf{x}_j^T \gamma^* - \eta < 0), \\
\tilde{U}_p^+(\eta, \gamma^*, \beta^*) &\equiv \frac{1}{n} \sum_{j \in I_1} K_{h_1}^+(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*) \text{pr}(Y_j - \mathbf{x}_j^T \gamma^* - \eta < 0 | \mathbf{z}_j^T \beta^*), \\
\tilde{U}_p^-(\eta, \gamma^*, \beta^*) &\equiv \frac{1}{n} \sum_{j \in I_1} K_{h_1}^-(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*) \text{pr}(Y_j - \mathbf{x}_j^T \gamma^* - \eta < 0 | \mathbf{z}_j^T \beta^*),
\end{aligned}$$

where, for $j \in I_1$,

$$\begin{aligned}
K_{h_1}^+(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*) &\equiv \begin{cases} K_{h_1}(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*), & K_{h_1}(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*) \geq 0, \\ 0, & K_{h_1}(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*) < 0. \end{cases} \\
K_{h_1}^-(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*) &\equiv \begin{cases} -K_{h_1}(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*), & K_{h_1}(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*) \leq 0, \\ 0, & K_{h_1}(\mathbf{z}_j^T \beta^* - \mathbf{z}_i^T \beta^*) > 0. \end{cases}
\end{aligned}$$

It is obvious that

$$\begin{aligned}
\tilde{U}(\cdot, \gamma^*, \beta^*) &= \tilde{U}^+(\cdot, \gamma^*, \beta^*) - \tilde{U}^-(\cdot, \gamma^*, \beta^*), \\
\tilde{U}_p(\cdot, \gamma^*, \beta^*) &= \tilde{U}_p^+(\cdot, \gamma^*, \beta^*) - \tilde{U}_p^-(\cdot, \gamma^*, \beta^*), \\
T_n(\eta, \gamma^*, \beta^*) &= \tilde{U}^+(\eta, \gamma^*, \beta^*) - \tilde{U}^-(\eta, \gamma^*, \beta^*) - \tilde{U}\{g(\mathbf{z}_i^T \beta^*), \gamma^*, \beta^*\} \\
&\quad - [\tilde{U}_p^+(\eta, \gamma^*, \beta^*) - \tilde{U}_p^-(\eta, \gamma^*, \beta^*) - \tilde{U}_p\{g(\mathbf{z}_i^T \beta^*), \gamma^*, \beta^*\}]. \tag{S4.1}
\end{aligned}$$

Define $b_n \equiv \lceil 1/h_1 \rceil$. The interval $[g(\mathbf{z}_i^T \boldsymbol{\beta}^*) - a_n, g(\mathbf{z}_i^T \boldsymbol{\beta}^*) + a_n]$ is divided into $2b_n$ equal intervals:

$$J_{n,r} = [g(\mathbf{z}_i^T \boldsymbol{\beta}^*) + ra_n/b_n, g(\mathbf{z}_i^T \boldsymbol{\beta}^*) + (r+1)a_n/b_n] = [\eta_{n,r}, \eta_{n,r+1}],$$

$r = -b_n, \dots, -1, 0, 1, \dots, b_n - 1$, each length a_n/b_n satisfies $k(n, h_1)h_1 \log n /$

$(1 + h_1) \leq a_n/b_n \leq k(n, h_1)h_1 \log n$. Finally, define

$$\begin{aligned} & \tilde{F}^*\{g(\mathbf{z}_i^T \boldsymbol{\beta}^*), \boldsymbol{\gamma}^*, \boldsymbol{\beta}\} \\ \equiv & \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) \text{pr}\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma}^* - g(\mathbf{z}_i^T \boldsymbol{\beta}^*) < 0 | \mathbf{x}_j, \mathbf{z}_j\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})}, \\ \Delta(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) = & \tilde{F}\{g(\mathbf{z}_i^T \boldsymbol{\beta}^*), \boldsymbol{\gamma}^*, \boldsymbol{\beta}\} - \tilde{F}\{g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}, \boldsymbol{\beta}\} \\ & - [\tilde{F}^*\{g(\mathbf{z}_i^T \boldsymbol{\beta}^*), \boldsymbol{\gamma}^*, \boldsymbol{\beta}\} - \tilde{F}^*\{g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}, \boldsymbol{\beta}\}]. \end{aligned}$$

We now prove three lemmas which will be used to prove Theorem 2.

Lemma 3. Under the Regularity Conditions C3, C4 and C5, we have

$$T_n^{*-}(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) \equiv \sup_{|\eta - g(\mathbf{z}_i^T \boldsymbol{\beta}^*)| \leq a_n} |T_n^-(\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)| = O_p\{k(n, h_1)h_1 \log n\},$$

for any $\boldsymbol{\beta}^*$ and $\boldsymbol{\gamma}^*$ satisfying $\|\boldsymbol{\beta}^* - \boldsymbol{\beta}\| \leq Cn^{-1/2}$, $\|\boldsymbol{\gamma}^* - \boldsymbol{\gamma}\| \leq Cn^{-1/2}$.

Proof. By the monotonicity of $\tilde{U}^-(\cdot, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)$ and $\tilde{U}_p^-(\cdot, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)$, for $\eta \in J_{n,r} = [\eta_{n,r}, \eta_{n,r+1}]$,

we get

$$\begin{aligned} & \tilde{U}^-\{\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\} - \tilde{U}^-\{g(\mathbf{z}_i^T \boldsymbol{\beta}^*), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\} - [\tilde{U}_p^-\{\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\} \\ & - \tilde{U}_p^-\{g(\mathbf{z}_i^T \boldsymbol{\beta}^*), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\}] \leq T_n^-(\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) \leq \tilde{U}^-\{\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\} \\ & - \tilde{U}^-\{g(\mathbf{z}_i^T \boldsymbol{\beta}^*), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\} - [\tilde{U}_p^-\{\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\} - \tilde{U}_p^-\{g(\mathbf{z}_i^T \boldsymbol{\beta}^*), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\}]. \end{aligned}$$

This can be written as

$$T_n^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \alpha_{nr}^- \leq T_n^-\{\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\} \leq T_n^-(\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) + \alpha_{nr}^-,$$

where $\alpha_{nr}^- = \tilde{U}_p^-(\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \tilde{U}_p^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)$. Hence

$$T_n^{*-}(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) \leq \max_{-b_n \leq r \leq b_n} |T_n^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)| + \max_{-b_n \leq r \leq b_n-1} \alpha_{nr}^-. \quad (\text{S4.2})$$

It is easy to show that

$$\max_{-b_n \leq r \leq b_n-1} \alpha_{nr}^- = O_p\{k(n, h_1)h_1 \log n\}. \quad (\text{S4.3})$$

Let $\mathcal{A} = \sigma(\mathbf{z}_1^T \boldsymbol{\beta}^*, \mathbf{z}_2^T \boldsymbol{\beta}^*, \dots, \mathbf{z}_n^T \boldsymbol{\beta}^*)$. For notational brevity, let

$$\begin{aligned} L_{nj}^- &\equiv K_{h_1}^-(\mathbf{z}_j^T \boldsymbol{\beta}^* - \mathbf{z}_i^T \boldsymbol{\beta}^*)([I(Y_j - \mathbf{x}_j^T \boldsymbol{\gamma}^* - \eta_{n,r} < 0) \\ &\quad - I\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma}^* - g(\mathbf{z}_i^T \boldsymbol{\beta}^*) < 0\}] - [\text{pr}(Y_j - \mathbf{x}_j^T \boldsymbol{\gamma}^* - \eta_{n,r} < 0 | \mathbf{z}_j^T \boldsymbol{\beta}^*) \\ &\quad - \text{pr}\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma}^* - g(\mathbf{z}_i^T \boldsymbol{\beta}^*) < 0 | \mathbf{z}_j^T \boldsymbol{\beta}^*\}]). \end{aligned}$$

Then,

$$T_n^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) = \frac{1}{n} \sum_{j \in I_1} L_{nj}^-.$$

By Bernstein inequality on page 95 of Serfling (1980), we have

$$\begin{aligned} &\text{pr}\{|T_n^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)| \geq k(n, h_1)h_1 \log n | \mathcal{A}\} \\ &\leq 2 \exp\left[-\frac{\{nk(n, h_1)h_1^2 \log n\}^2}{2 \sum_{j \in I_1} \text{var}(h_1 L_{nj}^- | \mathcal{A}) + 4C_1 nk(n, h_1)h_1^2 \log n / 3}\right]. \end{aligned} \quad (\text{S4.4})$$

By simple derivation, we get

$$\text{var}(h_1 L_{nj}^- | \mathcal{A}) = E\{h_1^2 (L_{nj}^-)^2 | \mathcal{A}\} \leq C_2 h_1^2 \{K_{h_1}^-(\mathbf{z}_j^T \boldsymbol{\beta}^* - \mathbf{z}_i^T \boldsymbol{\beta}^*)\}^2 |\eta_{n,r} - g(\mathbf{z}_i^T \boldsymbol{\beta}^*)|.$$

The above inequality holds under Condition C3. Then, under Conditions C4 and C5, it can be shown that

$$\sum_{j \in I_1} \text{var}(h_1 L_{nj}^- | \mathcal{A}) \leq C_3 n h_1 |\eta_{n,r} - g(\mathbf{z}_i^T \boldsymbol{\beta}^*)| \leq C_3 n h_1 k(n, h_1) \log n.$$

Then, under Condition C4, we have

$$\begin{aligned} & \frac{\{nk(n, h_1) h_1^2 \log n\}^2}{2 \sum_{j \in I_1} \text{var}(h_1 L_{nj}^- | \mathcal{A}) + 4 C_1 n k(n, h_1) h_1^2 \log n / 3} \\ & \geq C_4 \{nk(n, h_1) h_1^2 \log n\}^2 / \{nk(n, h_1) h_1 \log n\} = C_4 n h_1^3 k(n, h_1) \log n. \end{aligned} \quad (\text{S4.5})$$

Also we have

$$\begin{aligned} & \text{pr}\left\{\max_{-b_n \leq r \leq b_n} |T_n^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)| \geq k(n, h_1) h_1 \log n\right\} \\ & \leq 2b_n \max_{-b_n \leq r \leq b_n} \text{pr}\{|T_n^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)| \geq k(n, h_1) h_1 \log n\} \\ & = 2b_n \max_{-b_n \leq r \leq b_n} E[\text{pr}\{|T_n^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)| \geq k(n, h_1) h_1 \log n | \mathcal{A}\}]. \end{aligned} \quad (\text{S4.6})$$

Then combining (S4.4), (S4.5), and (S4.6), recalling that $b_n = \lceil h_1^{-1} \rceil$, we get

$$\begin{aligned} & \text{pr}\left\{\max_{-b_n \leq r \leq b_n} |T_n^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)| \geq k(n, h_1) h_1 \log n\right\} \\ & \leq 2(h_1^{-1} + 1) \exp\{-C_4 n h_1^3 k(n, h_1) \log n\} \leq 3 \exp\{-\log h_1 - C_4 n h_1^3 k(n, h_1) \log n\}, \end{aligned}$$

which goes to zero under C4. Combining this result, (S4.2) and (S4.3), Lemma 3 is proved.

Lemma 4. Under the Regularity Conditions C3, C4 and C5, we have

$$T_n^*(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) \equiv \sup_{|\eta - g(\mathbf{z}_i^T \boldsymbol{\beta}^*)| \leq a_n} |T_n(\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)| = O_p\{k(n, h_1)h_1 \log n\},$$

for any $\boldsymbol{\beta}^*$ and $\boldsymbol{\gamma}^*$ satisfying $\|\boldsymbol{\beta}^* - \boldsymbol{\beta}\| \leq Cn^{-1/2}$, $\|\boldsymbol{\gamma}^* - \boldsymbol{\gamma}\| \leq Cn^{-1/2}$.

Proof. By the monotonicity of $\tilde{U}^+(\cdot, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)$, $\tilde{U}^-(\cdot, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)$, $\tilde{U}_p^+(\cdot, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)$ and $\tilde{U}_p^-(\cdot, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)$, for $\eta \in J_{n,r} = [\eta_{n,r}, \eta_{n,r+1}]$, we have

$$\begin{aligned} \tilde{U}^+(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) &\leq \tilde{U}^+(\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) \leq \tilde{U}^+(\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*), \\ \tilde{U}^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) &\leq \tilde{U}^-(\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) \leq \tilde{U}^-(\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*), \\ \tilde{U}_p^+(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) &\leq \tilde{U}_p^+(\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) \leq \tilde{U}_p^+(\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*), \\ \tilde{U}_p^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) &\leq \tilde{U}_p^-(\eta, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) \leq \tilde{U}_p^-(\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*). \end{aligned}$$

Then we have

$$\begin{aligned} &\tilde{U}^+(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \tilde{U}^-(\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \{\tilde{U}_p^+(\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) \\ &- \tilde{U}_p^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)\} \leq \tilde{U}^+(\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \tilde{U}^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) \\ &- \{\tilde{U}_p^+(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \tilde{U}_p^-(\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)\}. \end{aligned} \tag{S4.7}$$

Note that

$$\begin{aligned} &\tilde{U}^+(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \tilde{U}^-(\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \{\tilde{U}_p^+(\eta_{n,r+1}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \tilde{U}_p^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)\} \\ &= \tilde{U}(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \tilde{U}_p(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) - \alpha_{nr}, \end{aligned}$$

and

$$\begin{aligned} & \tilde{U}^+(\eta_{n,r+1}, \gamma^*, \beta^*) - \tilde{U}^-(\eta_{n,r}, \gamma^*, \beta^*) - \{\tilde{U}_p^+(\eta_{n,r}, \gamma^*, \beta^*) \\ & - \tilde{U}_p^-(\eta_{n,r+1}, \gamma^*, \beta^*)\} = \tilde{U}(\eta_{n,r+1}, \gamma^*, \beta^*) - \tilde{U}_p(\eta_{n,r+1}, \gamma^*, \beta^*) + \alpha_{nr}, \end{aligned}$$

where $\alpha_{nr} = \tilde{U}^-(\eta_{n,r+1}, \gamma^*, \beta^*) - \tilde{U}^-(\eta_{n,r}, \gamma^*, \beta^*) + \tilde{U}_p^+(\eta_{n,r+1}, \gamma^*, \beta^*) - \tilde{U}_p^+(\eta_{n,r}, \gamma^*, \beta^*)$ and $\alpha_{nr} \geq 0$. Combining the above results, (S4.1), (S4.7) and the definition of $T_n(\cdot, \gamma^*, \beta^*)$, we get

$$T_n(\eta_{n,r}, \gamma^*, \beta^*) - \alpha_{nr} \leq T_n\{\eta, \gamma^*, \beta^*\} \leq T_n(\eta_{n,r+1}, \gamma^*, \beta^*) + \alpha_{nr}.$$

Hence

$$T_n^*(\gamma^*, \beta^*) \leq \max_{-b_n \leq r \leq b_n} |T_n(\eta_{n,r}, \gamma^*, \beta^*)| + \max_{-b_n \leq r \leq b_n-1} \alpha_{nr}. \quad (\text{S4.8})$$

Note that α_{nr} can be written as

$$\begin{aligned} \alpha_{nr} &= T_n^-(\eta_{n,r+1}, \gamma^*, \beta^*) - T_n^-(\eta_{n,r}, \gamma^*, \beta^*) + \{\tilde{U}_p^+(\eta_{n,r+1}, \gamma^*, \beta^*) \\ & - \tilde{U}_p^+(\eta_{n,r}, \gamma^*, \beta^*)\} + \{\tilde{U}_p^-(\eta_{n,r+1}, \gamma^*, \beta^*) - \tilde{U}_p^-(\eta_{n,r}, \gamma^*, \beta^*)\}. \end{aligned}$$

Combining the above relation, Lemma 3, and Conditions C3, C4 and C5, we get

$$\max_{-b_n \leq r \leq b_n-1} \alpha_{nr} = O_p\{k(n, h_1)h_1 \log n\}. \quad (\text{S4.9})$$

For notational brevity, let

$$\begin{aligned}
L_{nj} &\equiv K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta}^* - \mathbf{z}_i^T \boldsymbol{\beta}^*)([I(Y_j - \mathbf{x}_j^T \boldsymbol{\gamma}^* - \eta_{n,r} < 0) \\
&\quad - I\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma}^* - g(\mathbf{z}_i^T \boldsymbol{\beta}^*) < 0\}] - [\text{pr}(Y_j - \mathbf{x}_j^T \boldsymbol{\gamma}^* - \eta_{n,r} < 0 | \mathbf{z}_j^T \boldsymbol{\beta}^*) \\
&\quad - \text{pr}\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma}^* - g(\mathbf{z}_i^T \boldsymbol{\beta}^*) < 0 | \mathbf{z}_j^T \boldsymbol{\beta}^*\}]).
\end{aligned}$$

Then,

$$T_n(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) = \frac{1}{n} \sum_{j \in I_1} L_{nj}.$$

Similar to the analysis of $T_n^-(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)$ in Lemma 3, we can get

$$\text{pr}\left\{\max_{-b_n \leq r \leq b_n} |T_n(\eta_{n,r}, \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)| \geq k(n, h_1) h_1 \log n\right\} \leq 3 \exp\{-\log h_1 - C_4 n h_1^3 k(n, h_1) \log n\},$$

which goes to zero under C4. Combining this result, (S4.8) and (S4.9), Lemma 4 is proved.

Lemma 5. Under the Regularity Conditions C1, C3, C4 and C5,

$$\sup_{\substack{\|\boldsymbol{\beta}^* - \boldsymbol{\beta}\| \leq Cn^{-1/2} \\ \|\boldsymbol{\gamma}^* - \boldsymbol{\gamma}\| \leq Cn^{-1/2}}} |\Delta(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*)| = o_p(n^{-1/2}).$$

Proof. For notational brevity, let

$$\begin{aligned}
&s_j(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \boldsymbol{\gamma}, \boldsymbol{\beta}, \mathbf{z}_i) \\
&= K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})([I\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma}^* - g(\mathbf{z}_i^T \boldsymbol{\beta}^*) < 0\} \\
&\quad - I\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma} - g(\mathbf{z}_i^T \boldsymbol{\beta}) < 0\}] - [\text{pr}\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma}^* - g(\mathbf{z}_i^T \boldsymbol{\beta}^*) < 0 | \mathbf{x}_j, \mathbf{z}_j\} \\
&\quad - \text{pr}\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma} - g(\mathbf{z}_i^T \boldsymbol{\beta}) < 0 | \mathbf{x}_j, \mathbf{z}_j\}])
\end{aligned}$$

and $\delta'_j = \mathbf{x}_j^\top (\boldsymbol{\gamma}^* - \boldsymbol{\gamma}) + \{g(\mathbf{z}_i^\top \boldsymbol{\beta}^*) - g(\mathbf{z}_i^\top \boldsymbol{\beta})\}$.

$$\begin{aligned}
 & E[\sup_{\mathcal{D}} |s_j(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \boldsymbol{\gamma}, \boldsymbol{\beta}, \mathbf{z}_i)|^2] \\
 = & E[K_{h_1}^2 (\mathbf{z}_j^\top \boldsymbol{\beta} - \mathbf{z}_i^\top \boldsymbol{\beta}) \sup_{\mathcal{D}} |I\{\epsilon_j < \delta'_j + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta})\} \\
 & - I\{\epsilon_j < g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta})\} - F_\epsilon\{\delta'_j + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\} \\
 & + F_\epsilon\{g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\}|^2] \\
 \leq & Ch_1^{-2} E[\sup_{\mathcal{D}} |I\{\epsilon_j < |\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta})\} \\
 & - I\{\epsilon_j < -|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta})\} - F_\epsilon\{-|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\} \\
 & + F_\epsilon\{|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\}|^2] \\
 \leq & 2Ch_1^{-2} E\{\sup_{\mathcal{D}} ([I\{\epsilon_j < |\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta})\} \\
 & - I\{\epsilon_j < -|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta})\}]^2 + [F_\epsilon\{|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\} \\
 & - F_\epsilon\{-|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\}]^2)\} \\
 = & 2Ch_1^{-2} E\{\sup_{\mathcal{D}} ([I\{\epsilon_j < |\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta})\} \\
 & - I\{\epsilon_j < -|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta})\}] + [F_\epsilon\{|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\} \\
 & - F_\epsilon\{-|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\}]^2)\} \\
 = & 2Ch_1^{-2} E\{\sup_{\mathcal{D}} (F_\epsilon\{|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\} \\
 & - F_\epsilon\{-|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\} + [F_\epsilon\{|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\} \\
 & - F_\epsilon\{-|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\}]^2)\} \\
 \leq & 6Ch_1^{-2} E\left(\sup_{\mathcal{D}} \left[F_\epsilon\{|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\} \right. \right. \\
 & \left. \left. - F_\epsilon\{-|\delta'_j| + g(\mathbf{z}_i^\top \boldsymbol{\beta}) - g(\mathbf{z}_j^\top \boldsymbol{\beta}), \mathbf{x}_j, \mathbf{z}_j\}\right]\right) \\
 \leq & C'h_1^{-2} E(\sup_{\mathcal{D}} |\delta'_j|)
 \end{aligned}$$

$$\leq C' h_1^{-2} E[\sup_{\mathcal{D}} \|\mathbf{x}_j\| \|\boldsymbol{\gamma}^* - \boldsymbol{\gamma}\| + |g(\mathbf{z}_i^T \boldsymbol{\beta}^*) - g(\mathbf{z}_i^T \boldsymbol{\beta})|] = O_p\{(nh_1^4)^{-1/2}\}. \quad (\text{S4.10})$$

In the above derivation, the first inequality uses the monotonicity of indicator function and $F_\epsilon(\cdot, \mathbf{x}_j, \mathbf{z}_j)$, as well as Condition C5. The fourth inequality uses Condition C3. The last equality uses Conditions C1 and C9. Note that $E\{\sup_{\mathcal{D}} |s_j(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \boldsymbol{\gamma}, \boldsymbol{\beta}, \mathbf{z}_i)|^2\}$ actually does not depend on j , and, under Condition C4, we can get

$$\max_{j \in I_1} E\{\sup_{\mathcal{D}} |s_j(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \boldsymbol{\gamma}, \boldsymbol{\beta}, \mathbf{z}_i)|^2\} = E\{\sup_{\mathcal{D}} |s_j(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \boldsymbol{\gamma}, \boldsymbol{\beta}, \mathbf{z}_i)|^2\} \leq C, \quad (\text{S4.11})$$

$$\begin{aligned} & \sum_{j \in I_1} E\{\sup_{\mathcal{D}} |s_j(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \boldsymbol{\gamma}, \boldsymbol{\beta}, \mathbf{z}_i)|^2\} \\ = & n E\{\sup_{\mathcal{D}} |s_j(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \boldsymbol{\gamma}, \boldsymbol{\beta}, \mathbf{z}_i)|^2\} = O_p\{n(nh_1^4)^{-1/2}\}, \end{aligned} \quad (\text{S4.12})$$

where C is a constant. By Markov's inequality and (S4.10), we get

$$\sup_{\mathcal{D}} |s_j(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \boldsymbol{\gamma}, \boldsymbol{\beta}, \mathbf{z}_i)|^2 = O_p\{(nh_1^4)^{-1/2}\}.$$

Then we get

$$\sum_{j \in I_1} \sup_{\mathcal{D}} |s_j(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \boldsymbol{\gamma}, \boldsymbol{\beta}, \mathbf{z}_i)|^2 = n \sup_{\mathcal{D}} |s_j(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \boldsymbol{\gamma}, \boldsymbol{\beta}, \mathbf{z}_i)|^2 = O_p\{n(nh_1^4)^{-1/2}\}. \quad (\text{S4.13})$$

Based on (S4.11), (S4.12), (S4.13) and Lemma 3.3 of He and Shao (2000), we get

$$\sup_{\mathcal{D}} \left| \sum_{j \in I_1} s_j(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \boldsymbol{\gamma}, \boldsymbol{\beta}, \mathbf{z}_i) \right| = O_p\{n^{1/2}(nh_1^4)^{-1/4}(\log n)^{1/2}\}.$$

By Condition C4, Lemma 5 is shown.

Proof of Theorem 2. By Theorem 1, Lemma 4 and the convergence rate of $\tilde{\boldsymbol{\beta}}$ and $\tilde{\boldsymbol{\gamma}}$, we

have

$$T_n\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} = O_p\{k(n, h_1)h_1 \log n\}.$$

So under Conditions C2, C4, C5 and the consistency of $\tilde{\boldsymbol{\beta}}$, we have

$$\begin{aligned} & \tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} - \tilde{F}\{g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} - [\tilde{F}_p\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} - \tilde{F}_p\{g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\}] \\ = & T_n\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} / \left\{ \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) / n \right\} = O_p\{k(n, h_1)h_1 \log n\}, \end{aligned}$$

where

$$\begin{aligned} & \tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} \\ = & \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) I\{Y_j - \mathbf{x}_j^T \tilde{\gamma} - \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}) < 0\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})} = \tau, \\ & \tilde{F}\{g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} = \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) I\{Y_j - \mathbf{x}_j^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) < 0\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})}, \\ & \tilde{F}_p\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} \\ = & \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) \text{pr}\{Y_j - \mathbf{x}_j^T \tilde{\gamma} - \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}) < 0 | \mathbf{z}_j^T \tilde{\boldsymbol{\beta}}\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})}, \\ & \tilde{F}_p\{g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} \\ = & \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) \text{pr}\{Y_j - \mathbf{x}_j^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) < 0 | \mathbf{z}_j^T \tilde{\boldsymbol{\beta}}\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})}. \end{aligned}$$

Because

$$\begin{aligned} & \tilde{F}_p\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} - \tilde{F}_p\{g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} \\ = & f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) \{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}) - g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}})\} + O_p\{k(n, h_1)^2\}, \end{aligned}$$

hence

$$\begin{aligned}
& \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}) - g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) \\
&= \{f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta})\}^{-1} [\tilde{F}_p\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} - \tilde{F}_p\{g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\}] + O_p\{k(n, h_1)^2\} \\
&= \{f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta})\}^{-1} [\tilde{F}\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} - \tilde{F}\{g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} \\
&\quad - T_n\{\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\gamma}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} / \{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})/n\}] + O_p\{k(n, h_1)^2\} \\
&= \{f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta})\}^{-1} [\tau - \tilde{F}\{g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\}] + O_p\{k(n, h_1)h_1 \log n\}. \tag{S4.14}
\end{aligned}$$

The last equality holds under Condition C4.

By direct calculation, we have

$$\begin{aligned}
& \tilde{F}\{g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} \\
&= \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) I\{Y_j - \mathbf{x}_j^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) < 0\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})} \\
&\quad + \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) I\{Y_j - \mathbf{x}_j^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) < 0\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})} \\
&\quad \times \frac{\sum_{j \in I_1} \{K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) - K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})}.
\end{aligned}$$

Thus,

$$\begin{aligned}
& \tilde{F}\{g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}), \tilde{\gamma}, \tilde{\boldsymbol{\beta}}\} - \tilde{F}\{g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}), \tilde{\gamma}, \boldsymbol{\beta}\} \\
&= \frac{\sum_{j \in I_1} \{K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) - K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})\} I\{Y_j - \mathbf{x}_j^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) < 0\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})} \\
&\quad + \frac{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) I\{Y_j - \mathbf{x}_j^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) < 0\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})} \\
&\quad \times \frac{\sum_{j \in I_1} \{K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) - K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})\}}{\sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \tilde{\boldsymbol{\beta}} - \mathbf{z}_i^T \tilde{\boldsymbol{\beta}})}
\end{aligned}$$

$$= A_1 + A_2. \quad (\text{S4.15})$$

Similar to the derivation of (S3.12) and (S3.13) from (S3.9), we get

$$\begin{aligned} A_1 &= \frac{\text{pr}\{Y_i - \mathbf{x}_i^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\beta}) < 0 | \mathbf{z}_i^T \tilde{\beta}\} f(\mathbf{z}_i^T \tilde{\beta}) - \text{pr}\{Y_i - \mathbf{x}_i^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\beta}) < 0 | \mathbf{z}_i^T \beta\} f(\mathbf{z}_i^T \beta)}{f(\mathbf{z}_i^T \beta)} \\ &\quad + o_p(n^{-1/2}) + O_p(h_1^4), \\ A_2 &= \frac{\text{pr}\{Y_i - \mathbf{x}_i^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\beta}) < 0 | \mathbf{z}_i^T \tilde{\beta}\} \{f(\mathbf{z}_i^T \beta) - f(\mathbf{z}_i^T \tilde{\beta})\}}{f(\mathbf{z}_i^T \beta)} + o_p(n^{-1/2}) + O_p(h_1^4) \\ &= \frac{\text{pr}\{Y_i - \mathbf{x}_i^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\beta}) < 0 | \mathbf{z}_i^T \beta\} \{f(\mathbf{z}_i^T \beta) - f(\mathbf{z}_i^T \tilde{\beta})\}}{f(\mathbf{z}_i^T \beta)} + o_p(n^{-1/2}) + O_p(h_1^4). \end{aligned}$$

Then, under Condition C4, we have

$$\begin{aligned} &A_1 + A_2 \quad (\text{S4.16}) \\ &= \text{pr}\{Y_i - \mathbf{x}_i^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\beta}) < 0 | \mathbf{z}_i^T \tilde{\beta}\} - \text{pr}\{Y_i - \mathbf{x}_i^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\beta}) < 0 | \mathbf{z}_i^T \beta\} + o_p(n^{-1/2}). \end{aligned}$$

Note that for any $i \in I_2$,

$$\begin{aligned} &\text{pr}\{Y_i - \mathbf{x}_i^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\beta}) < 0 | \mathbf{z}_i^T \tilde{\beta}\} \\ &= \tau + E\{f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i) \mathbf{x}_i^T | \mathbf{z}_i^T \beta\} (\tilde{\gamma} - \gamma) + g'(\mathbf{z}_i^T \beta) E(\mathbf{z}_{-1,i}^T | \mathbf{z}_i^T \beta) (\tilde{\beta}_{-1} - \beta_{-1}) + o_p(n^{-1/2}), \end{aligned}$$

and

$$\begin{aligned} &\text{pr}\{Y_i - \mathbf{x}_i^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\beta}) < 0 | \mathbf{z}_i^T \beta\} \\ &= \tau + E\{f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i) \mathbf{x}_i^T | \mathbf{z}_i^T \beta\} (\tilde{\gamma} - \gamma) + g'(\mathbf{z}_i^T \beta) E(\mathbf{z}_{-1,i}^T | \mathbf{z}_i^T \beta) (\tilde{\beta}_{-1} - \beta_{-1}) + o_p(n^{-1/2}). \end{aligned}$$

Thus

$$\text{pr}\{Y_i - \mathbf{x}_i^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\beta}) < 0 | \mathbf{z}_i^T \tilde{\beta}\} - \text{pr}\{Y_i - \mathbf{x}_i^T \tilde{\gamma} - g(\mathbf{z}_i^T \tilde{\beta}) < 0 | \mathbf{z}_i^T \beta\} = o_p(n^{-1/2}). \quad (\text{S4.17})$$

Combining (S4.15), (S4.16) and (S4.17), we get

$$\tilde{F}\{g(\mathbf{z}_i^T \tilde{\beta}), \tilde{\gamma}, \tilde{\beta}\} - \tilde{F}\{g(\mathbf{z}_i^T \tilde{\beta}), \tilde{\gamma}, \beta\} = o_p(n^{-1/2}). \quad (\text{S4.18})$$

By (S4.14) and (S4.18), we get

$$\begin{aligned} \tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}) - g(\mathbf{z}_i^T \tilde{\beta}) &= \{f_{\epsilon | \mathbf{z}^T \beta}(0, \mathbf{z}_i^T \beta)\}^{-1} [\tau - \tilde{F}\{g(\mathbf{z}_i^T \tilde{\beta}), \tilde{\gamma}, \beta\}] \\ &\quad + o_p(n^{-1/2}) + O_p\{k(n, h_1)h_1 \log n\}, \end{aligned} \quad (\text{S4.19})$$

Combining $\Delta(\tilde{\gamma}, \tilde{\beta}) = o_p(n^{-1/2})$ from Lemma 5 and (S4.19), we obtain

$$\begin{aligned} &\tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}) - g(\mathbf{z}_i^T \tilde{\beta}) \\ &= \{f_{\epsilon | \mathbf{z}^T \beta}(0, \mathbf{z}_i^T \beta)\}^{-1} [\tau - \tilde{F}\{g(\mathbf{z}_i^T \tilde{\beta}), \gamma, \beta\}] \\ &\quad - \{f_{\epsilon | \mathbf{z}^T \beta}(0, \mathbf{z}_i^T \beta)\}^{-1} [\tilde{F}^*\{g(\mathbf{z}_i^T \tilde{\beta}), \tilde{\gamma}, \beta\} - \tilde{F}^*\{g(\mathbf{z}_i^T \tilde{\beta}), \gamma, \beta\}] + o_p(n^{-1/2}). \end{aligned} \quad (\text{S4.20})$$

Also we can show

$$\begin{aligned} &\tilde{F}^*\{g(\mathbf{z}_i^T \tilde{\beta}), \tilde{\gamma}, \beta\} \\ &= \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \beta - \mathbf{z}_i^T \beta) \text{pr}[\epsilon_j < \mathbf{x}_j^T (\tilde{\gamma} - \gamma) + \{g(\mathbf{z}_i^T \tilde{\beta}) - g(\mathbf{z}_i^T \beta)\} \\ &\quad + \{g(\mathbf{z}_i^T \beta) - g(\mathbf{z}_j^T \beta)\} | \mathbf{x}_j, \mathbf{z}_j] / \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \beta - \mathbf{z}_i^T \beta), \end{aligned}$$

and

$$\begin{aligned} \tilde{F}^*\{g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}, \boldsymbol{\beta}\} &= \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) \text{pr}\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{x}_j, \mathbf{z}_j\} \\ &\quad / \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}). \end{aligned}$$

Then combining the above results, under Conditions C1 and C2, we have

$$\begin{aligned} &\tilde{F}^*\{g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}), \tilde{\boldsymbol{\gamma}}, \boldsymbol{\beta}\} - \tilde{F}^*\{g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}, \boldsymbol{\beta}\} \\ &= E\{f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i) \mathbf{x}_i^T | \mathbf{z}_i^T \boldsymbol{\beta}\} (\tilde{\boldsymbol{\gamma}} - \boldsymbol{\gamma}) + g'(\mathbf{z}_i^T \boldsymbol{\beta}) E\{f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i) \mathbf{z}_{-1,i}^T | \mathbf{z}_i^T \boldsymbol{\beta}\} \\ &\quad \times (\tilde{\boldsymbol{\beta}}_{-1} - \boldsymbol{\beta}_{-1}) + o_p(n^{-1/2}). \end{aligned} \tag{S4.21}$$

Combining (S4.20) and (S4.21), we get

$$\begin{aligned} &\tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\boldsymbol{\gamma}}) - g(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}) \\ &= \{f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta})\}^{-1} [\tau - \tilde{F}\{g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}, \boldsymbol{\beta}\}] \\ &\quad - \{f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta})\}^{-1} E\{f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i) \mathbf{x}_i^T | \mathbf{z}_i^T \boldsymbol{\beta}\} (\tilde{\boldsymbol{\gamma}} - \boldsymbol{\gamma}) \\ &\quad - \{f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta})\}^{-1} g'(\mathbf{z}_i^T \boldsymbol{\beta}) E\{f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i) \mathbf{z}_{-1,i}^T | \mathbf{z}_i^T \boldsymbol{\beta}\} (\tilde{\boldsymbol{\beta}}_{-1} - \boldsymbol{\beta}_{-1}) + o_p(n^{-1/2}). \end{aligned}$$

Theorem 2 is proved.

S5 Partial Results for the Proof of Theorem 3

We first state a result regarding $g'(\mathbf{z}^T \boldsymbol{\beta})$.

Proposition 2. Under the Regularity Conditions C1, C3, C4, C5-C8, we have

$$\tilde{g}'(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\boldsymbol{\gamma}}) - g'(\mathbf{z}_i^T \boldsymbol{\beta}) = o_p(1),$$

for all $\mathbf{z}_i \in I_2$.

The proof of Proposition 2 is similar to that of Theorem 2, so we omit it here.

The following five lemmas are used to prove Lemma 11.

Lemma 6. Under the Regularity Conditions C1, C3 and C4,

$$\sup_{\mathcal{D}} \left\| \frac{1}{m} \sum_{i \in I_2} \eta_{mi} \{ \boldsymbol{\gamma}, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*) \} \right\| = o_p(m^{-1/2}).$$

Proof. For convenience, denote $\delta_i \equiv \mathbf{x}_i^T (\boldsymbol{\gamma}^* - \boldsymbol{\gamma}) + \{ \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*) - g(\mathbf{z}_i^T \boldsymbol{\beta}) \}$. First, by the definition of $\eta_{mi}(\cdot)$ and $G_i(\cdot)$,

$$\begin{aligned} & E[\sup_{\mathcal{D}} \|\eta_{mi} \{ \boldsymbol{\gamma}, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*) \} \|^2] \\ &= E[P(\mathbf{x}_i, \mathbf{z}_i)^T P(\mathbf{x}_i, \mathbf{z}_i) \frac{f_{\epsilon}^{*2}(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau^2(1-\tau)^2} \sup_{\mathcal{D}} |I\{Y_i - \mathbf{x}_i^T \boldsymbol{\gamma}^* - \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*) < 0\} \\ &\quad - I\{Y_i - \mathbf{x}_i^T \boldsymbol{\gamma} - g(\mathbf{z}_i^T \boldsymbol{\beta}) < 0\} \\ &\quad - F_{\epsilon}([\mathbf{x}_i^T (\boldsymbol{\gamma}^* - \boldsymbol{\gamma}) + \{ \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*) - g(\mathbf{z}_i^T \boldsymbol{\beta}) \}], \mathbf{x}_i, \mathbf{z}_i) + \tau|^2] \\ &= E[P(\mathbf{x}_i, \mathbf{z}_i)^T P(\mathbf{x}_i, \mathbf{z}_i) \frac{f_{\epsilon}^{*2}(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau^2(1-\tau)^2} \\ &\quad \times \sup_{\mathcal{D}} |I\{\epsilon_i + \mathbf{x}_i^T \boldsymbol{\gamma} + g(\mathbf{z}_i^T \boldsymbol{\beta}) - \mathbf{x}_i^T \boldsymbol{\gamma}^* - \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*) < 0\} - I(\epsilon_i < 0) \\ &\quad - F_{\epsilon}([\mathbf{x}_i^T (\boldsymbol{\gamma}^* - \boldsymbol{\gamma}) + \{ \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*) - g(\mathbf{z}_i^T \boldsymbol{\beta}) \}], \mathbf{x}_i, \mathbf{z}_i) + F_{\epsilon}(0, \mathbf{x}_i, \mathbf{z}_i)|^2] \\ &= E[P(\mathbf{x}_i, \mathbf{z}_i)^T P(\mathbf{x}_i, \mathbf{z}_i) \frac{f_{\epsilon}^{*2}(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau^2(1-\tau)^2} \sup_{\mathcal{D}} |I(\epsilon_i < \delta_i) - I(\epsilon_i < 0) \\ &\quad - F_{\epsilon}(\delta_i, \mathbf{x}_i, \mathbf{z}_i) + F_{\epsilon}(0, \mathbf{x}_i, \mathbf{z}_i)|^2] \end{aligned}$$

$$\begin{aligned}
 &\leq CE \left\{ \sup_{\mathcal{D}} |I(\epsilon_i < |\delta_i|) - I(\epsilon_i < -|\delta_i|) - F_\epsilon(-|\delta_i|, \mathbf{x}_i, \mathbf{z}_i) + F_\epsilon(|\delta_i|, \mathbf{x}_i, \mathbf{z}_i)|^2 \right\} \\
 &\leq 2CE \left(\sup_{\mathcal{D}} [\{I(\epsilon_i < |\delta_i|) - I(\epsilon_i < -|\delta_i|)\}^2 + \{F_\epsilon(|\delta_i|, \mathbf{x}_i, \mathbf{z}_i) - F_\epsilon(-|\delta_i|, \mathbf{x}_i, \mathbf{z}_i)\}^2] \right) \\
 &= 2CE \left(\sup_{\mathcal{D}} [I(\epsilon_i < |\delta_i|) - I(\epsilon_i < -|\delta_i|) + \{F_\epsilon(|\delta_i|, \mathbf{x}_i, \mathbf{z}_i) - F_\epsilon(-|\delta_i|, \mathbf{x}_i, \mathbf{z}_i)\}^2] \right) \\
 &= 2CE \left(\sup_{\mathcal{D}} [F_\epsilon(|\delta_i|, \mathbf{x}_i, \mathbf{z}_i) - F_\epsilon(-|\delta_i|, \mathbf{x}_i, \mathbf{z}_i) + \{F_\epsilon(|\delta_i|, \mathbf{x}_i, \mathbf{z}_i) - F_\epsilon(-|\delta_i|, \mathbf{x}_i, \mathbf{z}_i)\}^2] \right) \\
 &\leq 6CE \left[\sup_{\mathcal{D}} \{F_\epsilon(|\delta_i|, \mathbf{x}_i, \mathbf{z}_i) - F_\epsilon(-|\delta_i|, \mathbf{x}_i, \mathbf{z}_i)\} \right] \\
 &\leq C'E(\sup_{\mathcal{D}} |\delta_i|) \\
 &\leq C'E[\sup_{\mathcal{D}} \|\mathbf{x}_i\| \|\boldsymbol{\gamma}^* - \boldsymbol{\gamma}\| + |\tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*) - g(\mathbf{z}_i^T \boldsymbol{\beta})|] \\
 &= O_p\{(nh_1)^{-1/2} + h_1^4\}. \tag{S5.22}
 \end{aligned}$$

In the above derivation, the first inequality uses the monotonicity of indicator function and $F_\epsilon(\cdot, \mathbf{x}_i, \mathbf{z}_i)$, as well as Condition C1 and the boundedness of the proposed $f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i)$. The fourth inequality uses Condition C3. The last equality uses Conditions C1, C4 and Theorem 1. Note that $E[\sup_{\mathcal{D}} \|\eta_{mi}\{\boldsymbol{\gamma}, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*)\}\|^2]$ actually does not depend on i , and, under Condition C4, we can get

$$\begin{aligned}
 &\max_{i \in I_2} E[\sup_{\mathcal{D}} \|\eta_{mi}\{\boldsymbol{\gamma}, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*)\}\|^2] \\
 &= E[\sup_{\mathcal{D}} \|\eta_{mi}\{\boldsymbol{\gamma}, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*)\}\|^2] \leq C, \tag{S5.23}
 \end{aligned}$$

$$\begin{aligned}
 &\sum_{i \in I_2} E[\sup_{\mathcal{D}} \|\eta_{mi}\{\boldsymbol{\gamma}, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*)\}\|^2] \\
 &= mE[\sup_{\mathcal{D}} \|\eta_{mi}\{\boldsymbol{\gamma}, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*)\}\|^2] \\
 &= O_p[m\{h_1^4 + (nh_1)^{-1/2}\}], \tag{S5.24}
 \end{aligned}$$

where C is a constant. By Markov's inequality and (S5.22), we get

$$\sup_{\mathcal{D}} \|\eta_{ni}\{\boldsymbol{\gamma}, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*)\}\|^2 = O_p\{h_1^4 + (nh_1)^{-1/2}\}.$$

Then we have

$$\begin{aligned} & \sum_{i \in I_2} \sup_{\mathcal{D}} \|\eta_{ni}\{\boldsymbol{\gamma}, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*)\}\|^2 \\ &= m \sup_{\mathcal{D}} \|\eta_{ni}\{\boldsymbol{\gamma}, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*)\}\|^2 \\ &= O_p[m\{h_1^4 + (nh_1)^{-1/2}\}]. \end{aligned} \tag{S5.25}$$

Based on (S5.23), (S5.24), (S5.25) and Lemma 3.3 of He and Shao (2000), we get

$$\begin{aligned} & \sup_{\mathcal{D}} \left\| \sum_{i \in I_2} \eta_{ni}\{\boldsymbol{\gamma}, \boldsymbol{\beta}, g(\mathbf{z}_i^T \boldsymbol{\beta}), \boldsymbol{\gamma}^*, \boldsymbol{\beta}^*, \tilde{g}(\mathbf{z}_i^T \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*)\} \right\| \\ &= O_p[m^{1/2}\{h_1^2 + (nh_1)^{-1/4}\}(\log m)^{1/2}]. \end{aligned}$$

By Condition C4, Lemma 6 is shown.

Lemma 7. Under the Regularity conditions C1, C2 and C4, we have

$$\frac{1}{m} \sum_{i \in I_2} [G_{pi}\{\tilde{\boldsymbol{\gamma}}, \tilde{\boldsymbol{\beta}}, \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\boldsymbol{\gamma}})\} - \tilde{G}_{pi}\{\tilde{\boldsymbol{\gamma}}, \tilde{\boldsymbol{\beta}}, \tilde{g}(\mathbf{z}_i^T \tilde{\boldsymbol{\beta}}, \tilde{\boldsymbol{\gamma}})\}] = o_p(m^{-1/2}).$$

Lemma 7 can be proven by combining a second-order Taylor series expansion and several inequalities hence is omitted.

Lemma 8. Let

$$W_{ns} \equiv \frac{1}{n} \sum_{j \in I_1} \frac{1}{m} \sum_{i \in I_2} \frac{f_{\epsilon}^*(0, \mathbf{x}_i, \mathbf{z}_i) f_{\epsilon}(0, \mathbf{x}_i, \mathbf{z}_i) P_s(\mathbf{x}_i, \mathbf{z}_i) K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})}{\tau(1 - \tau) f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) f_{\mathbf{z}^T \boldsymbol{\beta}}(\mathbf{z}_i^T \boldsymbol{\beta})}$$

$$\begin{aligned}
 & ([I\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta})\} - I(\epsilon_j < 0)] - \\
 & [\text{pr}\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}, \mathbf{z}_j^T \boldsymbol{\beta}\} - \text{pr}(\epsilon_j < 0 | \mathbf{z}_j^T \boldsymbol{\beta})]),
 \end{aligned}$$

where $P_s(\mathbf{x}_i, \mathbf{z}_i)$ is the s th element of $P(\mathbf{x}_i, \mathbf{z}_i)$. Under the Regularity Conditions C1-C5 and C9, we have $W_{ns} = o_p(n^{-1/2})$, for $s = 1, 2, \dots, d_\gamma + d_\beta - 1$.

Proof. For notational brevity, for $i \in I_2$, let

$$\begin{aligned}
 & L_{njs}(\mathbf{x}_i, \mathbf{z}_i, \boldsymbol{\beta}) \\
 \equiv & \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i) P_s(\mathbf{x}_i, \mathbf{z}_i) K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})}{\tau(1 - \tau) f_{\epsilon | \mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) f_{\mathbf{z}^T \boldsymbol{\beta}}(\mathbf{z}_i^T \boldsymbol{\beta})} \\
 & ([I\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta})\} - I(\epsilon_j < 0)] \\
 & - [\text{pr}\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}, \mathbf{z}_j^T \boldsymbol{\beta}\} - \text{pr}(\epsilon_j < 0 | \mathbf{z}_j^T \boldsymbol{\beta})]).
 \end{aligned}$$

Then,

$$W_{ns} = \frac{1}{n} \sum_{j \in I_1} \frac{1}{m} \sum_{i \in I_2} L_{njs}(\mathbf{x}_i, \mathbf{z}_i, \boldsymbol{\beta}).$$

Let $\mathcal{A} = \sigma(\mathbf{z}_j^T \boldsymbol{\beta}, j \in I_1, \mathbf{x}_i, \mathbf{z}_i, i \in I_2)$ and $c = 1/(2\alpha_1) + 1/4$. Note that under Condition C4, $c > 2$. By Bernstein inequality on page 95 of Serfling (1980), we have

$$\text{pr}(|W_{ns}| \geq h_1^c \log n | \mathcal{A}) \leq 2 \exp\left\{-\frac{(nh_1^{c+1} \log n)^2}{2 \sum_{j \in I_1} \text{var}(L_{njs} | \mathcal{A}) + 4C_1 nh_1^{c+1} \log n / 3}\right\},$$

where $L_{njs} = m^{-1} \sum_{i \in I_2} h_1 L_{njs}(\mathbf{x}_i, \mathbf{z}_i, \boldsymbol{\beta})$, $j \in I_1$ and $C_1 = \sup |h_1 L_{njs}(\mathbf{x}_i, \mathbf{z}_i, \boldsymbol{\beta})|$, which is a finite constant under Conditions C1, C2, C5 and C9. By simple derivation, we get

$$\text{var}(L_{njs} | \mathcal{A}) = E(L_{njs}^2 | \mathcal{A})$$

$$\begin{aligned}
 &= \frac{1}{m^2} \sum_{i \in I_2} h_1^2 E\{L_{njs}^2(\mathbf{x}_i, \mathbf{z}_i, \boldsymbol{\beta}) | \mathcal{A}\} \\
 &\quad + \frac{2}{m^2} \sum_{p \neq q, p, q \in I_2} h_1^2 E\{L_{njs}(\mathbf{x}_p, \mathbf{z}_p, \boldsymbol{\beta}) L_{njs}(\mathbf{x}_q, \mathbf{z}_q, \boldsymbol{\beta}) | \mathcal{A}\}. \tag{S5.26}
 \end{aligned}$$

Note that

$$\begin{aligned}
 &E\{([I\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta})\} - I(\epsilon_j < 0)] \\
 &\quad - [\text{pr}\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}, \mathbf{z}_j^T \boldsymbol{\beta}\} - \text{pr}(\epsilon_j < 0 | \mathbf{z}_j^T \boldsymbol{\beta})])^2 | \mathcal{A}\} \\
 &= |\text{pr}\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}, \mathbf{z}_j^T \boldsymbol{\beta}\} - \text{pr}(\epsilon_j < 0 | \mathbf{z}_j^T \boldsymbol{\beta})| \\
 &\quad \times [1 - |\text{pr}\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}, \mathbf{z}_j^T \boldsymbol{\beta}\} - \text{pr}(\epsilon_j < 0 | \mathbf{z}_j^T \boldsymbol{\beta})|].
 \end{aligned}$$

We first analyze the first term of (S5.26). We have

$$\begin{aligned}
 &\frac{1}{m^2} \sum_{i \in I_2} h_1^2 E\{L_{njs}^2(\mathbf{x}_i, \mathbf{z}_i, \boldsymbol{\beta}) | \mathcal{A}\} \\
 &\leq \frac{1}{m^2} \sum_{i \in I_2} h_1^2 K_{h_1}^2(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) \left\{ \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i) P_s(\mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau) f_{\epsilon | \mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) f_{\mathbf{z}^T \boldsymbol{\beta}}(\mathbf{z}_i^T \boldsymbol{\beta})} \right\}^2 \\
 &\quad \times |\text{pr}\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}, \mathbf{z}_j^T \boldsymbol{\beta}\} - \text{pr}(\epsilon_j < 0 | \mathbf{z}_j^T \boldsymbol{\beta})| \\
 &\leq \frac{C_2'}{m^2} \sum_{i \in I_2} h_1^2 K_{h_1}^2(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) |\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}| \\
 &\leq \frac{C_2''}{m^2} \sum_{i \in I_2} h_1^3 K_{h_1}^2(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) \\
 &= \frac{C_2'' h_1^2}{m} \left\{ \frac{1}{m h_1} \sum_{i \in I_2} h_1^2 K_{h_1}^2(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) \right\} \\
 &= \frac{C_2'' h_1^2}{m} \left[\int k^2(u) du f_{\mathbf{z}^T \boldsymbol{\beta}}(\mathbf{z}_j^T \boldsymbol{\beta}) + O_p\{k(n, h_1)\} \right] \\
 &\leq \frac{C_2 h_1^2}{m} \tag{S5.27}
 \end{aligned}$$

in probability, where C_2', C_2'' , and C_2 are constants. The second inequality holds under

Conditions C1, C2, C3 and C9, the third inequality holds under Condition C5, the second last equality holds under Condition C4 and C5, and the last inequality holds under Conditions C2 and C5. Next we analyze the second term of (S5.26). Similar as the first term,

$$\begin{aligned}
 & \frac{2}{m^2} \sum_{p \neq q, p, q \in I_2} h_1^2 E\{L_{njs}(\mathbf{x}_p, \mathbf{z}_p, \boldsymbol{\beta}) L_{njs}(\mathbf{x}_q, \mathbf{z}_q, \boldsymbol{\beta}) | \mathcal{A}\} \\
 & \leq \frac{C_3}{m^2} \sum_{p \neq q, p, q \in I_2} h_1^2 |K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_p^T \boldsymbol{\beta}) K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_q^T \boldsymbol{\beta})| \\
 & \quad \times [|\text{pr}\{\epsilon_j < g(\mathbf{z}_p^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_p^T \boldsymbol{\beta}, \mathbf{z}_j^T \boldsymbol{\beta}\} - \text{pr}(\epsilon_j < 0 | \mathbf{z}_j^T \boldsymbol{\beta})| \\
 & \quad + |\text{pr}\{\epsilon_j < g(\mathbf{z}_q^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_q^T \boldsymbol{\beta}, \mathbf{z}_j^T \boldsymbol{\beta}\} - \text{pr}(\epsilon_j < 0 | \mathbf{z}_j^T \boldsymbol{\beta})|] \\
 & \leq \frac{C_4}{m^2} \left\{ \sum_{i \in I_2} I(|\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}| \leq h_1) \right\}^2 h_1 \\
 & = C_4 h_1^3 \left\{ \frac{1}{mh_1} \sum_{i \in I_2} I(|\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}| \leq h_1) \right\}^2 \\
 & = C_4 h_1^3 [f_{\mathbf{z}^T \boldsymbol{\beta}}(\mathbf{z}_j^T \boldsymbol{\beta}) + O_p\{k(n, h_1)\}]^2 \\
 & \leq C_5 h_1^3
 \end{aligned}$$

in probability. The first inequality holds under Conditions C1, C2, C3, C5 and C9. The second inequality holds under Conditions C3, C5 and C9, the second last equality and the last inequality hold under Conditions C2 and C4. Then combining (S5.26), (S5.27) and (S5.28), we obtain

$$\sum_{j \in I_1} \text{var}(L_{njs} | \mathcal{A}) \leq \sum_{j \in I_1} \left(\frac{C_2 h_1^2}{m} + C_5 h_1^3 \right) \leq C_6 (h_1^2 + nh_1^3) \leq C_7 n h_1^3 \log n \quad (\text{S5.28})$$

in probability. Then we can get

$$\begin{aligned}
 \frac{(nh_1^{c+1} \log n)^2}{2 \sum_{j \in I_1} \text{var}(L_{njs} | \mathcal{A}) + 4C_1 n h_1^{c+1} \log n / 3} & \geq C_8 (nh_1^{c+1} \log n)^2 / n h_1^3 \log n \\
 & = C_8 n h_1^{2c-1} \log n \quad (\text{S5.29})
 \end{aligned}$$

in probability. Also we have

$$\text{pr}(|W_{ns}| \geq h_1^c \log n) = E\{\text{pr}(|W_{ns}| \geq h_1^c \log n | \mathcal{A})\}. \quad (\text{S5.30})$$

Then combining (S5.26), (S5.29), and (S5.30), we get

$$\text{pr}(|W_{ns}| \geq h_1^c \log n) \leq \exp(-C_8 n h_1^{2c-1} \log n)$$

which goes to zero under Condition C4. This means $W_{ns} = O_p(h_1^c \log n) = O_p(n^{-1/2-\alpha_1/4} \log n) = o_p(n^{-1/2})$. Lemma 8 is proved.

Lemma 9. Under the Regularity Conditions C1-C5 and C9, we have

$$\begin{aligned} & \frac{1}{m} \sum_{i \in I_2} \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau) f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta})} P(\mathbf{x}_i, \mathbf{z}_i) \tilde{F}\{g(\mathbf{z}_i^T \boldsymbol{\beta}), \gamma, \boldsymbol{\beta}\} \\ = & \frac{1}{m} \sum_{i \in I_2} \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau) f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) n^{-1} \sum_{k \in I_1} K_{h_1}(\mathbf{z}_k^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})} P(\mathbf{x}_i, \mathbf{z}_i) \\ & \frac{1}{n} \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) (I(\epsilon_j < 0) + [\text{pr}\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}, \mathbf{z}_j^T \boldsymbol{\beta}\} \\ & - \text{pr}(\epsilon_j < 0 | \mathbf{z}_j^T \boldsymbol{\beta})]) + o_p(n^{-1/2}). \end{aligned}$$

Lemma 9 can be proven by combining Lemma 8 and standard kernel regression analysis and is omitted.

Lemma 10. For notational brevity, let

$$\begin{aligned} W_n^* & \equiv \frac{1}{m} \sum_{i \in I_2} \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau) f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) n^{-1} \sum_{k \in I_1} K_{h_1}(\mathbf{z}_k^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})} P(\mathbf{x}_i, \mathbf{z}_i) \\ & \frac{\sqrt{m}}{n} \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) (\{\tau - I(\epsilon_j < 0)\} \\ & - [\text{pr}\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}, \mathbf{z}_j^T \boldsymbol{\beta}\} - \text{pr}(\epsilon_j < 0 | \mathbf{z}_j^T \boldsymbol{\beta})]). \end{aligned}$$

Under the Regularity Conditions C1, C2, C4, C5, C9 and C10, we have

$$W_n^* = \frac{\sqrt{m}}{n} \sum_{j \in I_1} \frac{E\{f_\epsilon^*(0, \mathbf{x}_j, \mathbf{z}_j) f_\epsilon(0, \mathbf{x}_j, \mathbf{z}_j) P(\mathbf{x}_j, \mathbf{z}_j) | \mathbf{z}_j^T \boldsymbol{\beta}\}}{\tau(1-\tau) f_\epsilon(0, \mathbf{z}_j^T \boldsymbol{\beta})} \psi_j\{\boldsymbol{\gamma}, g(\mathbf{z}_j^T \boldsymbol{\beta})\} + o_p(1),$$

where $\psi_j\{\boldsymbol{\gamma}, g(\mathbf{z}_j^T \boldsymbol{\beta})\} \equiv \tau - I\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma} - g(\mathbf{z}_j^T \boldsymbol{\beta}) < 0\} = \tau - I(\epsilon_j < 0)$.

Proof.

$$\begin{aligned} W_n^* &= \frac{1}{m} \sum_{i \in I_2} \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau) f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) f_{\mathbf{z}^T \boldsymbol{\beta}}(\mathbf{z}_i^T \boldsymbol{\beta})} P(\mathbf{x}_i, \mathbf{z}_i) \\ &\quad - \frac{\sqrt{m}}{n} \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) (\{\tau - I(\epsilon_j < 0)\} \\ &\quad - [\text{pr}\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}, \mathbf{z}_j^T \boldsymbol{\beta}\} - \text{pr}(\epsilon_j < 0 | \mathbf{z}_j^T \boldsymbol{\beta})]) \\ &\quad + \frac{1}{m} \sum_{i \in I_2} \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau) f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) f_{\mathbf{z}^T \boldsymbol{\beta}}(\mathbf{z}_i^T \boldsymbol{\beta})} P(\mathbf{x}_i, \mathbf{z}_i) \\ &\quad - \frac{\sqrt{m}}{n} \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) \frac{f_{\mathbf{z}^T \boldsymbol{\beta}}(\mathbf{z}_i^T \boldsymbol{\beta}) - n^{-1} \sum_{k \in I_1} K_{h_1}(\mathbf{z}_k^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})}{n^{-1} \sum_{k \in I_1} K_{h_1}(\mathbf{z}_k^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})} \\ &\quad \times (\{\tau - I(\epsilon_j < 0)\} - [\text{pr}\{\epsilon_j < g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_i^T \boldsymbol{\beta}, \mathbf{z}_j^T \boldsymbol{\beta}\} \\ &\quad - \text{pr}(\epsilon_j < 0 | \mathbf{z}_j^T \boldsymbol{\beta})]) = B_1 + B_2. \end{aligned} \tag{S5.31}$$

Note that

$$\begin{aligned} &\frac{1}{m} \sum_{i \in I_2} \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau) f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) f_{\mathbf{z}^T \boldsymbol{\beta}}(\mathbf{z}_i^T \boldsymbol{\beta})} P(\mathbf{x}_i, \mathbf{z}_i) \\ &\quad - \frac{\sqrt{m}}{n} \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) \psi_j\{\boldsymbol{\gamma}, g(\mathbf{z}_j^T \boldsymbol{\beta})\} \\ &= \frac{\sqrt{m}}{n} \sum_{j \in I_1} \frac{E\{f_\epsilon^*(0, \mathbf{x}_j, \mathbf{z}_j) f_\epsilon(0, \mathbf{x}_j, \mathbf{z}_j) P(\mathbf{x}_j, \mathbf{z}_j) | \mathbf{z}_j^T \boldsymbol{\beta}\}}{\tau(1-\tau) f_\epsilon(0, \mathbf{z}_j^T \boldsymbol{\beta})} \psi_j\{\boldsymbol{\gamma}, g(\mathbf{z}_j^T \boldsymbol{\beta})\} \\ &\quad + o_p(1). \end{aligned} \tag{S5.32}$$

The above equality is obtained by using standard kernel regression analysis and by noting

that $E[\psi_j\{\boldsymbol{\gamma}, g(\mathbf{z}_j^T \boldsymbol{\beta})\} \mid \mathbf{z}_j^T \boldsymbol{\beta}] = 0$. For notational brevity, let

$$S_{is}(\mathbf{z}_j^T \boldsymbol{\beta}) \equiv \frac{K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i) P_s(\mathbf{x}_i, \mathbf{z}_i)}{f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) f_{\mathbf{z}^T \boldsymbol{\beta}}(\mathbf{z}_i^T \boldsymbol{\beta})} \{g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta})\},$$

where $i \in I_2$, $j \in I_1$, and $s = 1, 2, \dots, d_\gamma + d_\beta - 1$. Let $\mathbf{S}_i(\mathbf{z}_j^T \boldsymbol{\beta}) = \{S_{i1}(\mathbf{z}_j^T \boldsymbol{\beta}), \dots, S_{id_\gamma + d_\beta - 1}(\mathbf{z}_j^T \boldsymbol{\beta})\}^T$.

Then we also have

$$\begin{aligned} & \frac{1}{m} \sum_{i \in I_2} \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau) f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) f_{\mathbf{z}^T \boldsymbol{\beta}}(\mathbf{z}_i^T \boldsymbol{\beta})} P(\mathbf{x}_i, \mathbf{z}_i) \\ & \frac{\sqrt{m}}{n} \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) [\text{pr}\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma} - g(\mathbf{z}_i^T \boldsymbol{\beta}) < 0 \mid \mathbf{z}_j^T \boldsymbol{\beta}\} \\ & - \text{pr}\{Y_j - \mathbf{x}_j^T \boldsymbol{\gamma} - g(\mathbf{z}_j^T \boldsymbol{\beta}) < 0 \mid \mathbf{z}_j^T \boldsymbol{\beta}\}] \\ & = \frac{1}{m} \sum_{i \in I_2} \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau) f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta}) f_{\mathbf{z}^T \boldsymbol{\beta}}(\mathbf{z}_i^T \boldsymbol{\beta})} P(\mathbf{x}_i, \mathbf{z}_i) \\ & \frac{\sqrt{m}}{n} \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta}) [f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_j^T \boldsymbol{\beta}) \{g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta})\} \\ & + 2^{-1} f'_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(g_{ij}^*, \mathbf{z}_j^T \boldsymbol{\beta}) \{g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta})\}^2] \\ & = \frac{\sqrt{m}}{n} \sum_{j \in I_1} \frac{f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_j^T \boldsymbol{\beta})}{\tau(1-\tau)} \frac{1}{m} \sum_{i \in I_2} \mathbf{S}_i(\mathbf{z}_j^T \boldsymbol{\beta}) \\ & + \frac{\sqrt{m}}{2n} \sum_{j \in I_1} \frac{1}{m} \sum_{i \in I_2} \{g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta})\} \mathbf{S}_i(\mathbf{z}_j^T \boldsymbol{\beta}) \frac{f'_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(g_{ij}^*, \mathbf{z}_j^T \boldsymbol{\beta})}{\tau(1-\tau)}, \end{aligned} \tag{S5.33}$$

where g_{ij}^* is between $g(\mathbf{z}_i^T \boldsymbol{\beta}) - g(\mathbf{z}_j^T \boldsymbol{\beta})$ and 0. By standard kernel regression analysis, under Conditions C5 and C10, we have

$$E\{S_{is}(\mathbf{z}_j^T \boldsymbol{\beta}) \mid \mathbf{z}_j^T \boldsymbol{\beta}\} = O_p(h_1^4). \tag{S5.34}$$

We can also get

$$\begin{aligned}
 E\{S_{is}^2(\mathbf{z}_j^T \boldsymbol{\beta}) | \mathbf{z}_j^T \boldsymbol{\beta}\} &\leq CE \left(\frac{K_{h_1}^2 (\mathbf{z}_j^T \boldsymbol{\beta} - \mathbf{z}_i^T \boldsymbol{\beta})}{f_{\mathbf{z}^T \boldsymbol{\beta}}(\mathbf{z}_i^T \boldsymbol{\beta})} (\mathbf{z}_i^T \boldsymbol{\beta} - \mathbf{z}_j^T \boldsymbol{\beta})^2 | \mathbf{z}_j^T \boldsymbol{\beta} \right) \\
 &= C \int \frac{K_{h_1}^2 (t - \mathbf{z}_j^T \boldsymbol{\beta})}{f_{\mathbf{z}^T \boldsymbol{\beta}}(t)} (t - \mathbf{z}_j^T \boldsymbol{\beta})^2 f_{\mathbf{z}^T \boldsymbol{\beta}}(t) dt \\
 &= C \int K^2(u)/h_1^2 (h_1 u)^2 h_1 du \leq C' h_1.
 \end{aligned} \tag{S5.35}$$

The first inequality holds under Conditions C1, C2, and C9, and the last inequality holds under Condition C5. By Chebyshev's inequality, we can get

$$\Pr\{|S_{is}(\mathbf{z}_j^T \boldsymbol{\beta})| \geq 1\} \leq E\{S_{is}^2(\mathbf{z}_j^T \boldsymbol{\beta})\} \leq C' h_1. \tag{S5.36}$$

Let $S_s(\mathbf{z}_j^T \boldsymbol{\beta}) = m^{-1} \sum_{i \in I_2} S_{is}(\mathbf{z}_j^T \boldsymbol{\beta})$, $j \in I_1$. Under Condition C4, (S5.35) and (S5.36), together with Lemma 18 (page 20), Lemma 25 (page 27), Lemma 28 (page 30), the proof of Lemma 33 (page 31-33) and theorem 37 (page 34) in Pollard (1984), yield

$$\sup_{\mathbf{z}_j} |S_s(\mathbf{z}_j^T \boldsymbol{\beta}) - ES_s(\mathbf{z}_j^T \boldsymbol{\beta})| = O_p(m^{-1/2} h_1^{1/2} \log m). \tag{S5.37}$$

By (S5.34) and (S5.37), we get

$$\begin{aligned}
 \sup_{\mathbf{z}_j} S_s(\mathbf{z}_j^T \boldsymbol{\beta}) &\leq \sup_{\mathbf{z}_j} |S(\mathbf{z}_j^T \boldsymbol{\beta}) - ES(\mathbf{z}_j^T \boldsymbol{\beta})| + \sup_{\mathbf{z}_j} |E\{S_s(\mathbf{z}_j^T \boldsymbol{\beta})\}| \\
 &= O_p(m^{-1/2} h_1^{1/2} \log m) + O_p(h_1^4).
 \end{aligned} \tag{S5.38}$$

By (S5.38), we get the first term of (S5.33) is $O_p(h_1^{1/2} \log m) + O_p(m^{1/2} h_1^4) = o_p(1)$ under Conditions C2 and C4. Similarly we can prove the second term of (S5.33) is $o_p(1)$. Combining

these results and (S5.33), we get

$$\begin{aligned}
& \frac{1}{m} \sum_{i \in I_2} \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau) f_{\epsilon|\mathbf{z}^\top \boldsymbol{\beta}}(0, \mathbf{z}_i^\top \boldsymbol{\beta}) f_{\mathbf{z}^\top \boldsymbol{\beta}}(\mathbf{z}_i^\top \boldsymbol{\beta})} P(\mathbf{x}_i, \mathbf{z}_i) \\
& \frac{\sqrt{m}}{n} \sum_{j \in I_1} K_{h_1}(\mathbf{z}_j^\top \boldsymbol{\beta} - \mathbf{z}_i^\top \boldsymbol{\beta}) [\text{pr}\{Y_j - \mathbf{x}_j^\top \boldsymbol{\gamma} - g(\mathbf{z}_i^\top \boldsymbol{\beta}) < 0 | \mathbf{z}_j^\top \boldsymbol{\beta}\} \\
& - \text{pr}\{Y_j - \mathbf{x}_j^\top \boldsymbol{\gamma} - g(\mathbf{z}_j^\top \boldsymbol{\beta}) < 0 | \mathbf{z}_j^\top \boldsymbol{\beta}\}] = o_p(1).
\end{aligned} \tag{S5.39}$$

By (S5.32) and (S5.39), we get

$$\begin{aligned}
B_1 &= \frac{\sqrt{m}}{n} \sum_{j \in I_1} \frac{E\{f_\epsilon^*(0, \mathbf{x}_j, \mathbf{z}_j) f_\epsilon(0, \mathbf{x}_j, \mathbf{z}_j) P(\mathbf{x}_j, \mathbf{z}_j) | \mathbf{z}_j^\top \boldsymbol{\beta}\}}{\tau(1-\tau) f_\epsilon(0, \mathbf{z}_j^\top \boldsymbol{\beta})} \psi_j\{\boldsymbol{\gamma}, g(\mathbf{z}_j^\top \boldsymbol{\beta})\} \\
&+ o_p(1).
\end{aligned} \tag{S5.40}$$

Using the results of (S5.40) and similar standard kernel regression analysis, we can get

$B_2 = o_p(1)$. Combining these results, (S5.31) and (S5.40), Lemma 10 is proved.

S6 Proof of Theorem 3

Lemma 11. Under the Regularity Conditions C1-C5, C9 and C10, we have

$$\begin{aligned}
& \frac{1}{\sqrt{m}} \sum_{i \in I_2} G_i\{\tilde{\boldsymbol{\gamma}}, \tilde{\boldsymbol{\beta}}, \tilde{g}(\mathbf{z}_i^\top \tilde{\boldsymbol{\beta}}, \tilde{\boldsymbol{\gamma}})\} \\
&= \frac{1}{\sqrt{m}} \sum_{i \in I_2} G_i\{\boldsymbol{\gamma}, \boldsymbol{\beta}, g(\mathbf{z}_i^\top \boldsymbol{\beta})\} - V \begin{pmatrix} \sqrt{m}(\tilde{\boldsymbol{\gamma}} - \boldsymbol{\gamma}) \\ \sqrt{m}(\tilde{\boldsymbol{\beta}}_{-1} - \boldsymbol{\beta}_{-1}) \end{pmatrix} \\
& - \frac{\sqrt{m}}{n} \sum_{j \in I_1} \frac{E\{f_\epsilon^*(0, \mathbf{x}_j, \mathbf{z}_j) f_\epsilon(0, \mathbf{x}_j, \mathbf{z}_j) P(\mathbf{x}_j, \mathbf{z}_j) | \mathbf{z}_j^\top \boldsymbol{\beta}\}}{\tau(1-\tau) f_{\epsilon|\mathbf{z}^\top \boldsymbol{\beta}}(0, \mathbf{z}_j^\top \boldsymbol{\beta})} \psi_j\{\boldsymbol{\gamma}, g(\mathbf{z}_j^\top \boldsymbol{\beta})\} \\
&+ o_p(1).
\end{aligned}$$

Lemma 11 can be proven by using Lemma 6, Lemma 7, Lemma 9, Lemma 10, the

convergence rate of $\tilde{\gamma}$ and $\tilde{\beta}$ and the law of large numbers.

Lemma 12. Under the Regularity Conditions C1, C3, C4, C5-C8, we have

$$\sup_{i \in I_2} \{\hat{P}(\mathbf{x}_i, \mathbf{z}_i) - P(\mathbf{x}_i, \mathbf{z}_i)\} = o_p(1).$$

Lemma 12 can be proven by combining the definitions of $\hat{P}(\mathbf{x}_i, \mathbf{z}_i)$ and $P(\mathbf{x}_i, \mathbf{z}_i)$, Proposition 2 and the standard kernel regression properties.

Lemma 13. Under the Regularity Conditions C1-C10, we have

$$\begin{aligned} & (\hat{V}_0)^{-1} \frac{1}{\sqrt{m}} \sum_{i \in I_2} \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau)} [\tau - I\{Y_i - \mathbf{x}_i^T \tilde{\gamma} - \tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma}) < 0\}] \hat{P}(\mathbf{x}_i, \mathbf{z}_i) \\ = & V_0^{-1} \frac{1}{\sqrt{m}} \sum_{i \in I_2} G_i\{\tilde{\gamma}, \tilde{\beta}, \tilde{g}(\mathbf{z}_i^T \tilde{\beta}, \tilde{\gamma})\} + o_p(1), \end{aligned}$$

where V_0 is defined in Section S2.

Lemma 13 can be proven by using Lemma 11, Lemma 12 and the similar proof of Lemma 12.

Lemma 14. Under the Regularity Conditions, C1-C10, we have

$$\begin{aligned} & \begin{pmatrix} \sqrt{m}(\hat{\gamma} - \gamma) \\ \sqrt{m}(\hat{\beta}_{-1} - \beta_{-1}) \end{pmatrix} \\ = & V_0^{-1}(V_0 - V) \begin{pmatrix} \sqrt{m}(\tilde{\gamma} - \gamma) \\ \sqrt{m}(\tilde{\beta}_{-1} - \beta_{-1}) \end{pmatrix} \\ & + V_0^{-1} \frac{1}{\sqrt{m}} \sum_{i \in I_2} \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1-\tau)} P(\mathbf{x}_i, \mathbf{z}_i) \psi_i\{\gamma, g(\mathbf{z}_i^T \beta)\} \\ & - V_0^{-1} \frac{\sqrt{m}}{n} \sum_{j \in I_1} \frac{E\{f_\epsilon^*(0, \mathbf{x}_j, \mathbf{z}_j) f_\epsilon(0, \mathbf{x}_j, \mathbf{z}_j) P(\mathbf{x}_j, \mathbf{z}_j) | \mathbf{z}_j^T \beta\}}{\tau(1-\tau) f_{\epsilon|\mathbf{z}^T \beta}(0, \mathbf{z}_j^T \beta)} \psi_j\{\gamma, g(\mathbf{z}_j^T \beta)\} \end{aligned}$$

$$+o_p(1).$$

Lemma 14 can be proven by Lemma 11 and Lemma 13.

Proof of Theorem 3. Repeating all the analysis for $\hat{\beta}_{-1}$ and $\hat{\gamma}$, we can get

$$\begin{aligned}
& \begin{pmatrix} \sqrt{n}(\hat{\gamma}' - \gamma) \\ \sqrt{n}(\hat{\beta}'_{-1} - \beta_{-1}) \end{pmatrix} \\
= & V_0^{-1}(V_0 - V) \begin{pmatrix} \sqrt{n}(\tilde{\gamma}' - \gamma) \\ \sqrt{n}(\tilde{\beta}'_{-1} - \beta_{-1}) \end{pmatrix} \\
& + V_0^{-1} \frac{1}{\sqrt{n}} \sum_{i \in I_1} \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1 - \tau)} P(\mathbf{x}_i, \mathbf{z}_i) \psi_i\{\gamma, g(\mathbf{z}_i^T \beta)\} \\
& - V_0^{-1} \frac{\sqrt{n}}{m} \sum_{j \in I_2} \frac{E\{f_\epsilon^*(0, \mathbf{x}_j, \mathbf{z}_j) f_\epsilon(0, \mathbf{x}_j, \mathbf{z}_j) P(\mathbf{x}_j, \mathbf{z}_j) | \mathbf{z}_j^T \beta\}}{\tau(1 - \tau) f_{\epsilon | \mathbf{z}^T \beta}(0, \mathbf{z}_j^T \beta)} \psi_j\{\gamma, g(\mathbf{z}_j^T \beta)\} \\
& + o_p(1), \tag{S6.41}
\end{aligned}$$

where $\hat{\gamma}'$ and $\hat{\beta}'_{-1}$ are the initial estimators of γ and β_{-1} based on the data from the group

I_2 . Combining Lemma 14 and (S6.41), we have

$$\begin{aligned}
& \sqrt{N} \begin{pmatrix} (\hat{\gamma} + \hat{\gamma}')/2 - \gamma \\ (\hat{\beta}_{-1} + \hat{\beta}'_{-1})/2 - \beta_{-1} \end{pmatrix} \\
= & V_0^{-1}(V_0 - V) \frac{\sqrt{N}}{2} \begin{pmatrix} (\tilde{\gamma} - \gamma) + (\tilde{\gamma}' - \gamma) \\ (\tilde{\beta}_{-1} - \beta_{-1}) + (\tilde{\beta}'_{-1} - \beta_{-1}) \end{pmatrix} \\
& + V_0^{-1} \frac{1}{\sqrt{N}} \sum_{i=1}^N \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1 - \tau)} P(\mathbf{x}_i, \mathbf{z}_i) \psi_i\{\gamma, g(\mathbf{z}_i^T \beta)\} \\
& - V_0^{-1} \frac{1}{\sqrt{N}} \sum_{j=1}^N \frac{E\{f_\epsilon^*(0, \mathbf{x}_j, \mathbf{z}_j) f_\epsilon(0, \mathbf{x}_j, \mathbf{z}_j) P(\mathbf{x}_j, \mathbf{z}_j) | \mathbf{z}_j^T \beta\}}{\tau(1 - \tau) f_{\epsilon | \mathbf{z}^T \beta}(0, \mathbf{z}_j^T \beta)} \psi_j\{\gamma, g(\mathbf{z}_j^T \beta)\} \\
& + o_p(1)
\end{aligned}$$

$$= V_0^{-1}\{(V_0 - V)M_1 + M_2 - M_3\} + o_p(1),$$

where M_1 satisfies

$$\begin{aligned} \frac{\sqrt{N}}{2} \begin{pmatrix} (\tilde{\gamma} - \gamma) + (\tilde{\gamma}' - \gamma) \\ (\tilde{\beta}_{-1} - \beta_{-1}) + (\tilde{\beta}'_{-1} - \beta_{-1}) \end{pmatrix} &= M_1 + o_p(1), \\ M_2 &= \frac{1}{\sqrt{N}} \sum_{i=1}^N \frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1 - \tau)} P(\mathbf{x}_i, \mathbf{z}_i) \psi_i\{\gamma, g(\mathbf{z}_i^T \boldsymbol{\beta})\}, \\ M_3 &= \frac{1}{\sqrt{N}} \sum_{j=1}^N \frac{E\{f_\epsilon^*(0, \mathbf{x}_j, \mathbf{z}_j) f_\epsilon(0, \mathbf{x}_j, \mathbf{z}_j) P(\mathbf{x}_j, \mathbf{z}_j) | \mathbf{z}_j^T \boldsymbol{\beta}\}}{\tau(1 - \tau) f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_j^T \boldsymbol{\beta})} \psi_j\{\gamma, g(\mathbf{z}_j^T \boldsymbol{\beta})\}. \end{aligned}$$

Write $J \equiv (V_0 - V)$. Then we get

$$\begin{pmatrix} \sqrt{N}(\bar{\gamma} - \gamma) \\ \sqrt{N}(\bar{\beta}_{-1} - \beta_{-1}) \end{pmatrix} \rightarrow N(0, \boldsymbol{\Sigma})$$

in distribution with

$$\begin{aligned} \boldsymbol{\Sigma} &= V_0^{-1}\{\text{cov}(JM_1) + \text{cov}(M_2) + \text{cov}(M_3) + 2\text{cov}(JM_1, M_2) \\ &\quad - 2\text{cov}(JM_1, M_3) - 2\text{cov}(M_2, M_3)\} V_0^{-1}, \end{aligned} \tag{S6.42}$$

where

$$\begin{aligned} \text{cov}(M_2) &= V_0, \\ \text{cov}(M_3) &= E \left(\frac{[E\{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i) P(\mathbf{x}_i, \mathbf{z}_i) | \mathbf{z}_i^T \boldsymbol{\beta}\}]^{\otimes 2}}{\tau(1 - \tau) f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}^2(0, \mathbf{z}_i^T \boldsymbol{\beta})} \right), \\ \text{cov}(M_2, M_3) &= E \left[\frac{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i)}{\tau(1 - \tau) f_{\epsilon|\mathbf{z}^T \boldsymbol{\beta}}(0, \mathbf{z}_i^T \boldsymbol{\beta})} P(\mathbf{x}_i, \mathbf{z}_i) E\{f_\epsilon^*(0, \mathbf{x}_i, \mathbf{z}_i) \right] \end{aligned}$$

$$f_\epsilon(0, \mathbf{x}_i, \mathbf{z}_i)P(\mathbf{x}_i, \mathbf{z}_i)|\mathbf{z}_i^T \boldsymbol{\beta}\}^T \Big].$$

Theorem 3 is proved.

Remark 1. We now provide the detailed form of M_1 and related quantities if the initial estimators of $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}_{-1}$ are obtained by the method proposed in Ma and He (2016). Theorem 2 in Ma and He (2016) provided the asymptotic results of the initial estimators of $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ under their parameterization. Using the delta method, we can obtain the corresponding results for $\tilde{\boldsymbol{\gamma}}$ and $\tilde{\boldsymbol{\beta}}_{-1}$. Specifically, let $\mathbf{D} \equiv \text{diag}(I_{d_\gamma \times d_\gamma}, \mathbf{A})$, $\mathbf{A} \equiv \|\tilde{\boldsymbol{\beta}}\|_2(-\tilde{\boldsymbol{\beta}}_{-1}, I_{(d_\beta-1) \times (d_\beta-1)})$, where $I_{(d_\beta-1) \times (d_\beta-1)}$ and $I_{d_\gamma \times d_\gamma}$ are identity matrices, and let

$$\Omega \equiv E\{f_\epsilon(0, \mathbf{x}, \mathbf{z})P^0(\mathbf{x}, \mathbf{z})^{\otimes 2}\}.$$

Note that D is matrix with full row rank and Ω is a positive definite matrix. Let D^+ satisfy $DD^+ = \mathbf{I}_{d_\beta+d_\gamma-1}$. Then, following Ma and He (2016),

$$\begin{aligned} & \begin{pmatrix} \sqrt{n}(\tilde{\boldsymbol{\gamma}} - \boldsymbol{\gamma}) \\ \sqrt{n}(\tilde{\boldsymbol{\beta}}_{-1} - \boldsymbol{\beta}_{-1}) \end{pmatrix} \\ &= D(D^T \Omega D)^+ D^T \frac{1}{\sqrt{n}} \sum_{j \in I_1} \psi_j\{\boldsymbol{\gamma}, g(\mathbf{z}_j^T \boldsymbol{\beta})\} P^0(\mathbf{x}_j, \mathbf{z}_j) + o_p(1) \\ &= \Omega^{-1} \frac{1}{\sqrt{n}} \sum_{j \in I_1} \psi_j\{\boldsymbol{\gamma}, g(\mathbf{z}_j^T \boldsymbol{\beta})\} P^0(\mathbf{x}_j, \mathbf{z}_j) + o_p(1). \end{aligned} \tag{S6.43}$$

By the same derivation, the corresponding results for $\tilde{\boldsymbol{\gamma}}'$ and $\tilde{\boldsymbol{\beta}}'_{-1}$ are

$$\begin{pmatrix} \sqrt{n}(\tilde{\boldsymbol{\gamma}}' - \boldsymbol{\gamma}) \\ \sqrt{n}(\tilde{\boldsymbol{\beta}}'_{-1} - \boldsymbol{\beta}_{-1}) \end{pmatrix}$$

$$= \Omega^{-1} \frac{1}{\sqrt{m}} \sum_{j \in I_2} \psi_j \{ \gamma, g(\mathbf{z}_j^T \boldsymbol{\beta}) \} P^0(\mathbf{x}_j, \mathbf{z}_j) + o_p(1). \quad (\text{S6.44})$$

Based on (S6.43) and (S6.44), we can get

$$\begin{aligned} & \frac{\sqrt{N}}{2} \begin{pmatrix} (\tilde{\gamma} - \gamma) + (\tilde{\gamma}' - \gamma) \\ (\tilde{\boldsymbol{\beta}}_{-1} - \boldsymbol{\beta}_{-1}) + (\tilde{\boldsymbol{\beta}}'_{-1} - \boldsymbol{\beta}_{-1}) \end{pmatrix} \\ &= \frac{1}{\sqrt{N}} \Omega^{-1} \sum_{j=1}^N \psi_j \{ \gamma, g(\mathbf{z}_j^T \boldsymbol{\beta}) \} P^0(\mathbf{x}_j, \mathbf{z}_j) + o_p(1). \end{aligned}$$

This means $M_1 = \Omega^{-1} \frac{1}{\sqrt{N}} \sum_{j=1}^N \psi_j \{ \gamma, g(\mathbf{z}_j^T \boldsymbol{\beta}) \} P^0(\mathbf{x}_j, \mathbf{z}_j)$. Then $\text{cov}(JM_1) = J\Omega'J^T$, where $\Omega' = \tau(1 - \tau)\Omega^{-1}E\{P^0(\mathbf{x}_j, \mathbf{z}_j)^{\otimes 2}\}\Omega^{-1}$.

$$\begin{aligned} \text{cov}(JM_1, M_2) &= J\Omega^{-1}E\left[f_{\epsilon}^*(0, \mathbf{x}_i, \mathbf{z}_i)P^0(\mathbf{x}_i, \mathbf{z}_i)P(\mathbf{x}_i, \mathbf{z}_i)^T\right], \\ \text{cov}(JM_1, M_3) &= J\Omega^{-1}E\left[P^0(\mathbf{x}_i, \mathbf{z}_i) \frac{E\{f_{\epsilon}^*(0, \mathbf{x}_i, \mathbf{z}_i)f_{\epsilon}(0, \mathbf{x}_i, \mathbf{z}_i)P(\mathbf{x}_i, \mathbf{z}_i)|\mathbf{z}_i^T\boldsymbol{\beta}\}^T}{f_{\epsilon|\mathbf{z}^T\boldsymbol{\beta}}(0, \mathbf{z}_i^T\boldsymbol{\beta})}\right]. \end{aligned}$$

S7 Figures for Setting 2 of Simulation 2

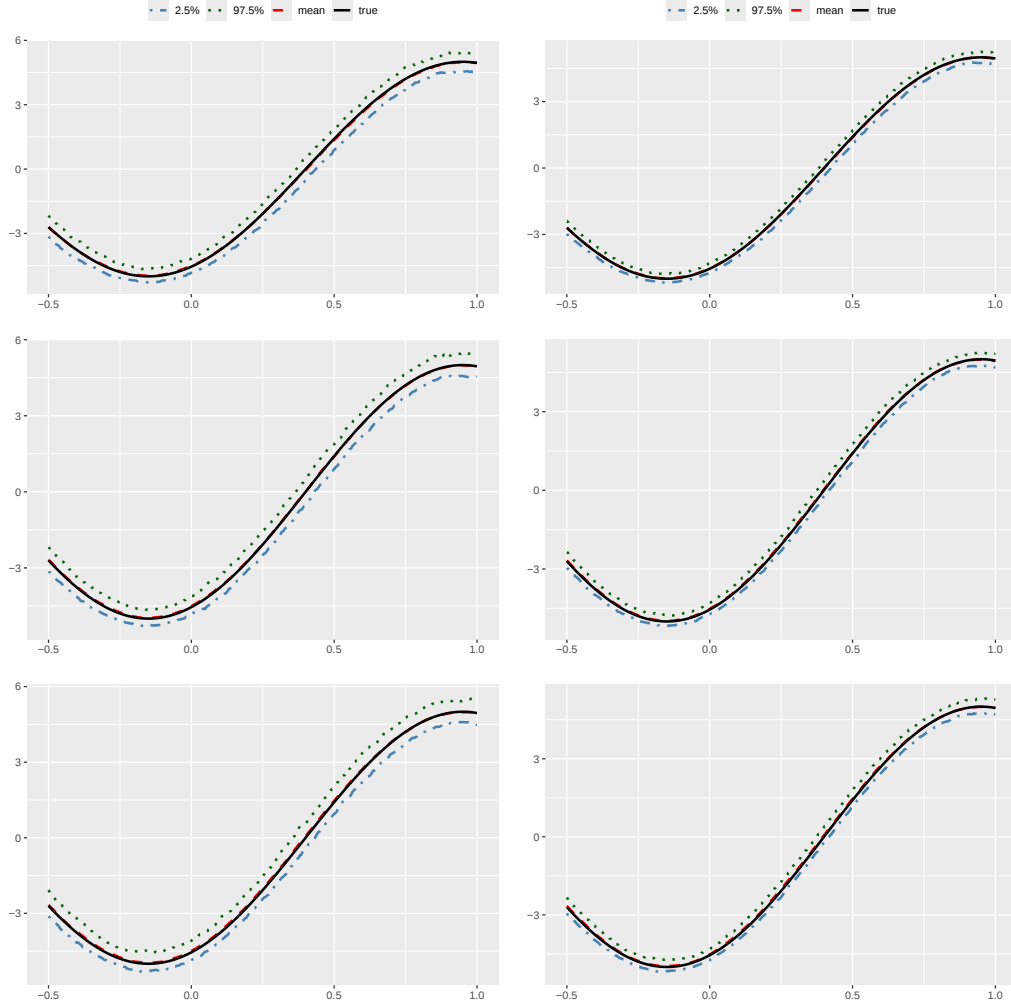


Figure S.1: Plots of estimators for $g(\cdot)$ in Simulation 2, Setting 2: The true error $\epsilon_i = \sigma(\mathbf{x}_i, \mathbf{z}_i)\{\tilde{\epsilon}_i - F^{-1}(\tau)\}$, where $\tilde{\epsilon}_i = F(\cdot)$ and $\sigma(\mathbf{x}_i, \mathbf{z}_i) = \sqrt{|\tilde{\mathbf{x}}_{i2}|}$. Estimation is based on our proposed method with the correct model $\tilde{\epsilon}_i \sim SN(0, 1, 3)$. Top to bottom panels: $\tau = 0.4, 0.5, 0.6$. Left panels: $n = 400$, right panels: $n = 1000$. The black solid lines are the true, the dashed red lines are the mean curve, the blue dot-dashed lines are 2.5% quantile, and the darkgreen dotted lines are 97.5% quantile.

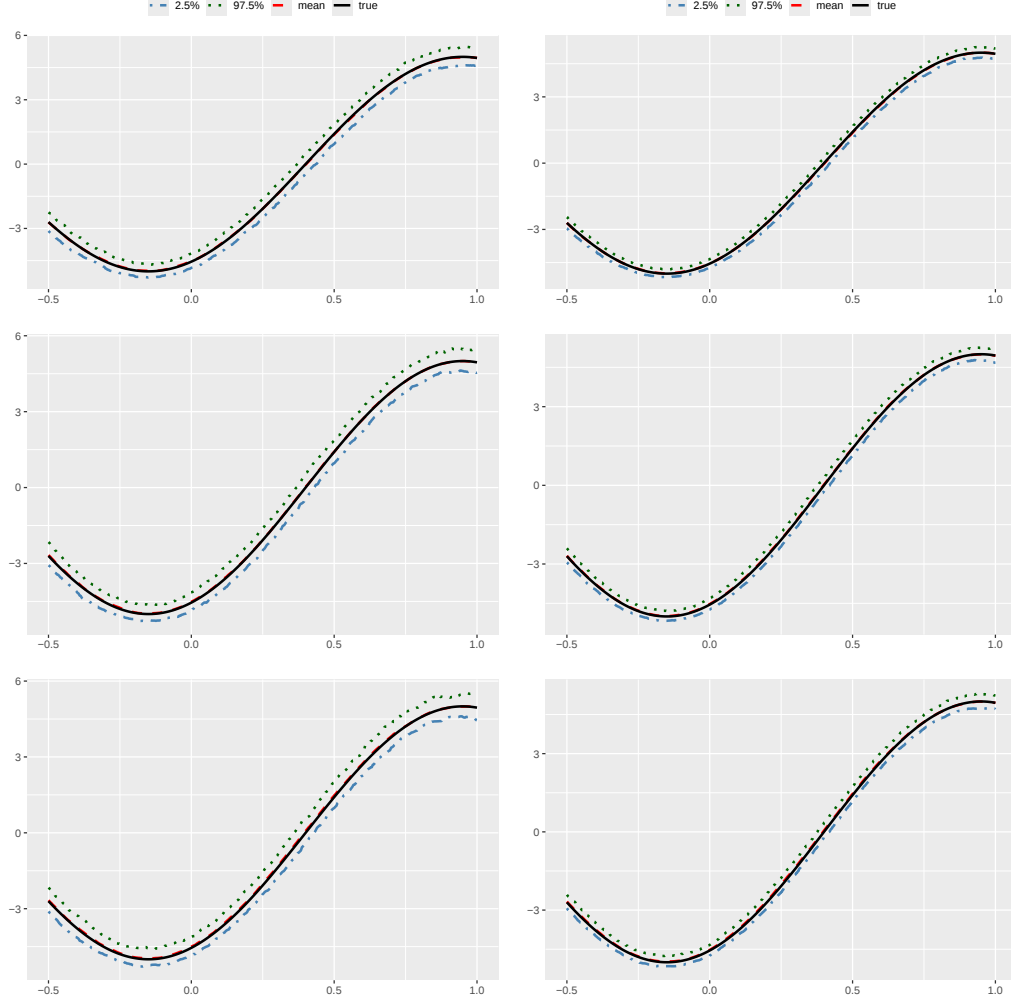


Figure S.2: Plots of estimators for $g(\cdot)$ in Simulation 2, Setting 2: The true error $\epsilon_i = \sigma(\mathbf{x}_i, \mathbf{z}_i)\{\tilde{\epsilon}_i - F^{-1}(\tau)\}$, where $\tilde{\epsilon}_i = F(\cdot)$ and $\sigma(\mathbf{x}_i, \mathbf{z}_i) = \sqrt{|\tilde{\mathbf{x}}_{i2}|}$. Estimation is based on our proposed method with the first misspecified error model $\tilde{\epsilon}_i^* \sim N(0, 1)$. Top to bottom panels: $\tau = 0.4, 0.5, 0.6$. Left panels: $n = 400$, right panels: $n = 1000$. The black solid lines are the true, the dashed red lines are the mean curve, the blue dot-dashed lines are 2.5% quantile, and the darkgreen dotted lines are 97.5% quantile.

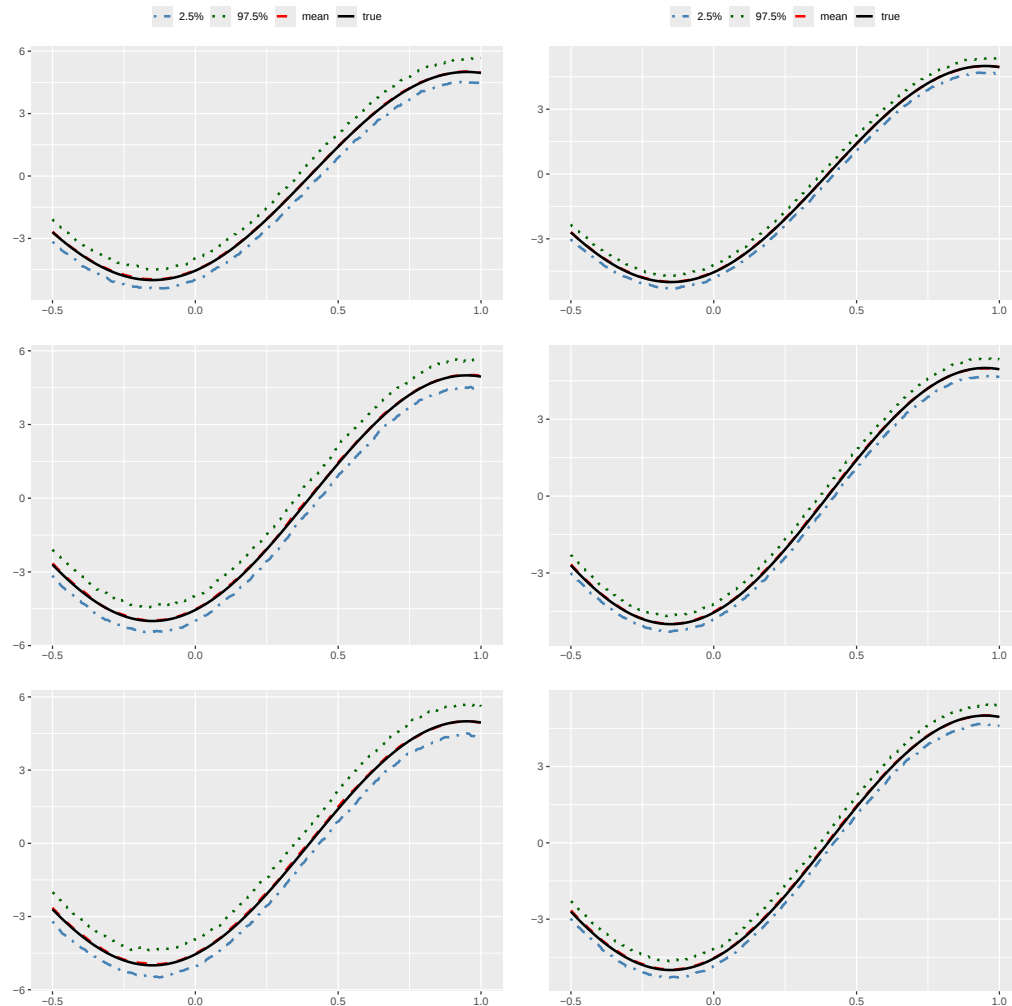


Figure S.3: Plots of estimators for $g(\cdot)$ in Simulation 2, Setting 2: The true error $\epsilon_i = \sigma(\mathbf{x}_i, \mathbf{z}_i)\{\tilde{\epsilon}_i - F^{-1}(\tau)\}$, where $\tilde{\epsilon}_i \sim F(\cdot)$ and $\sigma(\mathbf{x}_i, \mathbf{z}_i) = \sqrt{|\tilde{\mathbf{x}}_{i2}|}$. Estimation is based on our proposed method with the second misspecified error model $\tilde{\epsilon}_i^* \sim t_{(3)}$. Top to bottom panels: $\tau = 0.4, 0.5, 0.6$. Left panels: $n = 400$, right panels: $n = 1000$. The black solid lines are the true, the dashed red lines are the mean curve, the blue dot-dashed lines are 2.5% quantile, and the darkgreen dotted lines are 97.5% quantile.

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