

Supplementary Document for the Manuscript entitled “A Functional Single Index Model”

S1 Definition and Regularity Conditions

Let \mathcal{H} be the separable Hilbert space of square integrable functions on $[0, 1]$, and let $\langle \phi_1, \phi_2 \rangle \equiv \int_0^1 \phi_1(t)\phi_2(t)dt$ denote the inner product of the functions ϕ_1, ϕ_2 in \mathcal{H} . Then the L_2 norm $\|\cdot\|_2$ is the norm induced by the inner product. Let $\alpha(\cdot)$ be a function in \mathcal{H} . Let $\boldsymbol{\gamma}$ be the B-spline coefficient such that $\mathbf{B}_r(\cdot)^T \boldsymbol{\gamma}$ converges to $\alpha(\cdot)$, uniformly on $[0, 1]$ when the number of the B-spline inner knots goes to infinite, and $\mathbf{B}_r(\cdot)^T \boldsymbol{\gamma}_0$ converges to $\alpha_0(\cdot)$, the true function. Here $\mathbf{B}_r = (B_{r1}, \dots, B_{rd_\gamma})^T$ is the r th order B-spline basis vector. Note that for identifiability, we assumed $\alpha_0(0) = \mathbf{B}_r(0)^T \boldsymbol{\gamma}_0 = 1$, i.e., $\gamma_1 = B_{r1}(0)^{-1} \{1 - \sum_{k=2}^{d_\gamma} B_{rk}(0)\gamma_k\} = 1$. So we only have $d_\gamma - 1$ B-spline coefficients to estimate, and we denote $\boldsymbol{\gamma}^- = (\gamma_2, \dots, \gamma_{d_\gamma})^T$. Further, we denote $\boldsymbol{\alpha}(\mathbf{X}) = \int_0^1 \mathbf{X}(t)\alpha(t)dt$ and $\boldsymbol{\alpha}_0(\mathbf{X}) = \int_0^1 \mathbf{X}(t)\alpha_0(t)dt$. We denote the functional sup norm as $\|\cdot\|_\infty$, and the L_p norm as $\|\cdot\|_p$.

In addition, we define $\Gamma(\boldsymbol{\beta})$ to be a second moment based linear operator such that

$$\begin{aligned} \Gamma(\boldsymbol{\beta})\phi(t) &\equiv \int_0^1 E\{\boldsymbol{\beta}^T \mathbf{X}(t)\boldsymbol{\beta}^T \mathbf{X}(s)\}\phi(s)ds \\ &= E\{\langle \boldsymbol{\beta}^T \mathbf{X}, \phi \rangle \boldsymbol{\beta}^T \mathbf{X}(t)\} \end{aligned}$$

while its empirical version can be written as

$$\Gamma_n(\boldsymbol{\beta})\phi(t) \equiv n^{-1} \sum_{i=1}^n \langle \boldsymbol{\beta}^T \mathbf{X}_i, \phi \rangle \boldsymbol{\beta}^T \mathbf{X}_i(t).$$

Using these definitions, we can write

$$\langle \Gamma(\boldsymbol{\beta})B_{rk}, B_{rl} \rangle = E \left(\int_0^1 B_{rk}(t)\boldsymbol{\beta}^T \mathbf{X}_i(t)dt \int_0^1 B_{rl}(t)\boldsymbol{\beta}^T \mathbf{X}_i(t)dt \right),$$

$$\langle \Gamma_n(\boldsymbol{\beta})B_{rk}, B_{rl} \rangle = n^{-1} \sum_{i=1}^n \int_0^1 B_{rk}(t)\boldsymbol{\beta}^T \mathbf{X}_i(t)dt \int_0^1 B_{rl}(t)\boldsymbol{\beta}^T \mathbf{X}_i(t)dt.$$

Define $\mathbf{C}(\boldsymbol{\beta})$ as a $d_\gamma \times d_\gamma$ matrix with its (k, l) element $\langle \Gamma(\boldsymbol{\beta})B_{rk}, B_{rl} \rangle$, and $\widehat{\mathbf{C}}(\boldsymbol{\beta})$ as a $d_\gamma \times d_\gamma$ matrix with its (k, l) element $\langle \Gamma_n(\boldsymbol{\beta})B_{rk}, B_{rl} \rangle$. The locally efficient score function for $\boldsymbol{\beta}, \boldsymbol{\gamma}$ can be written as

$$\begin{aligned} & \mathbf{S}_{\text{eff}\boldsymbol{\beta}}(Y, \mathbf{Z}, \boldsymbol{\beta}, \boldsymbol{\gamma}, g^*) \\ &= [g^*(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}) - E\{g^*(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}) | \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}\}] \boldsymbol{\Theta}_\beta \{\mathbf{Z} - E(\mathbf{Z} | \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})\} \boldsymbol{\gamma}, \\ & \mathbf{S}_{\text{eff}\boldsymbol{\gamma}}(Y, \mathbf{Z}, \boldsymbol{\beta}, \boldsymbol{\gamma}, g^*) \\ &= [g^*(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}) - E\{g^*(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}) | \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}\}] \boldsymbol{\Theta}_\gamma \{\mathbf{Z} - E(\mathbf{Z} | \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})\}^T \boldsymbol{\beta}. \end{aligned}$$

Here $g^*(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}) = f_2^*(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}) / f^*(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})$, $f^*(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})$ is the possibly misspecified conditional density of Y given $\boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}$ and $f_2^*(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})$ is the derivative of $f^*(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})$ with respect to $\boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}$. When f is correctly specified, i.e. when $f^* = f$, we denote the resulting g^* as g . $\boldsymbol{\Theta}_\beta = (\mathbf{I}_{J-1}, \mathbf{0})$ and $\boldsymbol{\Theta}_\gamma = (\mathbf{0}, \mathbf{I}_{d_\gamma-1})$. Note that when $f^*(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}) = f(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})$, the true density function, the locally efficient score is the efficient score of (2). Throughout the text, $\mathbf{A}_1 = o_p(\mathbf{A}_2)$ for arbitrary vectors or matrices $\mathbf{A}_1, \mathbf{A}_2$ means that \mathbf{A}_1 has smaller order than \mathbf{A}_2 component wise.

We first list the regularity conditions under which we perform our theoretical analysis.

- (A1) The kernel function $K(\cdot)$ is non-negative, has compact support, and satisfies $\int K(s)ds = 1$, $\int K(s)sds = 0$ and $\int K(s)s^2ds < \infty$, and $\int K^2(s)ds < \infty$.
- (A2) The bandwidth h in the kernel smoothing satisfies $nh^2 \rightarrow \infty$ and $nh^8 \rightarrow 0$ when $n \rightarrow \infty$.
- (A3) Assume $\alpha_0 \in \{\alpha \in C^q([0, 1]), \alpha \text{ is one-to-one, and } \alpha_0(0) = 1\}$. The spline order $r \geq q$.
- (A4) We define the knots $t_{-r+1} \leq \dots \leq t_0 = 0$ and $t_{N+r} \geq \dots \geq t_{N+1} = 1$. Let N be the number of interior knots and $[0, 1]$ be divided into $N + 1$

subintervals. In this case, $d_\gamma = N + r$. Let h_p be the distance between the $(p+1)$ th and p th interior knots of the order r B-spline functions and let $h_b = \max_{r \leq p \leq N+r} h_p$. There exists a constant C_{h_b} , $0 < c_{h_b} < \infty$, such that

$$\max_{r \leq p \leq N+r} h_p = O(N^{-1}) \text{ and } h_b / \min_{r \leq p \leq N+r} h_p < c_{h_b},$$

where N is the number of knots which satisfies $N \rightarrow \infty$ as $n \rightarrow \infty$, and $N^{-1}n(\log n)^{-1} \rightarrow \infty$ and $Nn^{-1/(2q+1)} \rightarrow \infty$.

(A5) γ_0 is a spline coefficient such that $\sup_{t \in [0,1]} |\mathbf{B}_r(t)^\top \gamma_0 - \alpha_0(t)| = O_p(h_b^q)$. The existence of such γ_0 has been shown in De Boor (1978).

(A6) $X_j(\cdot), j = 1, \dots, J$ are continuous random functions in $t \in [0, 1]$. For each t , $|E\{X_j(t)\}| < \infty$. $\|\beta^\top \mathbf{X}(\cdot)\|_2$ is finite almost surely for any bounded β . $E\{\beta^\top \mathbf{X}_i(\cdot) \mid \beta^\top \mathbf{Z}_i \gamma\}$ and its first two derivatives have finite L_2 norm almost surely for any bounded β, γ . The second moment operator $\Gamma(\beta)$ is strictly positive definite.

(A7)

$$E[\{\mathbf{S}_{\text{eff}\beta}(Y_i, \mathbf{Z}_i, \beta, \gamma, g^*)^\top, \mathbf{S}_{\text{eff}\gamma}(Y_i, \mathbf{Z}_i, \beta, \gamma, g^*)^\top\}^\top]$$

is a smooth function of $(\beta^\top, \gamma^\top)^\top$ and has unique root for β, γ .

(A8) $f^*(Y, \beta^\top \mathbf{Z} \gamma)$ is a continuous density function and has bounded derivative with respect to the second argument. $f^*(Y, \beta^\top \mathbf{Z} \gamma)$ is bounded away from 0 and ∞ on its support. This implies $g^*(Y, \beta^\top \mathbf{Z} \gamma)$ is a continuous bounded function and $g^*(Y, \beta^\top \mathbf{Z} \gamma)$ is bounded away from 0 and ∞ on its support. Let $f_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)$ be the density for $\beta_0^\top \mathbf{Z} \gamma_0$. $f_{\mathbf{Z}}$ has two bounded derivatives, and $f_{\mathbf{Z}}$ is bounded away from 0 and ∞ on its support.

S2 Proofs of the propositions in the main text

S2.1 Proof of Proposition 1

Assume the problem is not identifiable. Then there exist $\{f, \beta, \alpha(t)\} \neq \{\tilde{f}, \tilde{\beta}, \tilde{\alpha}(t)\}$ such that

$$f \left\{ Y, \sum_{j=1}^J \beta_j \int_0^1 \alpha(t) X_j(t) dt \right\} = \tilde{f} \left\{ Y, \sum_{j=1}^J \tilde{\beta}_j \int_0^1 \tilde{\alpha}(t) X_j(t) dt \right\} \quad (\text{S1})$$

for all Y and all functions $X_1(\cdot), \dots, X_J(\cdot)$. Because (S1) holds for all $X_j(\cdot), j = 1, \dots, J$, it holds when $X_j(t) = 0$ for $j = 1, \dots, J - 1$ as well. Note that $\beta_J = \tilde{\beta}_J = 1$, we then have

$$f \left\{ Y, \int_0^1 \alpha(t) X_J(t) dt \right\} = \tilde{f} \left\{ Y, \int_0^1 \tilde{\alpha}(t) X_J(t) dt \right\}. \quad (\text{S2})$$

Let $X_J(t) = a(t) + \delta b(t)$ and let $\delta \rightarrow 0$, this yields

$$\begin{aligned} & f'_2 \left\{ Y, \int_0^1 \alpha(t) a(t) dt \right\} \int_0^1 \alpha(t) b(t) dt \\ &= \lim_{\delta \rightarrow 0} \left(f \left[Y, \int_0^1 \alpha(t) \{a(t) + \delta b(t)\} dt \right] - f \left\{ Y, \int_0^1 \alpha(t) a(t) dt \right\} \right) / \delta \\ &= \lim_{\delta \rightarrow 0} \left(\tilde{f} \left[Y, \int_0^1 \tilde{\alpha}(t) \{a(t) + \delta b(t)\} dt \right] - \tilde{f} \left\{ Y, \int_0^1 \tilde{\alpha}(t) a(t) dt \right\} \right) / \delta \\ &= \tilde{f}'_2 \left\{ Y, \int_0^1 \tilde{\alpha}(t) a(t) dt \right\} \int_0^1 \tilde{\alpha}(t) b(t) dt, \end{aligned} \quad (\text{S3})$$

where $f'_2(Y, \cdot), \tilde{f}'_2(Y, \cdot)$ denote the partial derivatives of f, \tilde{f} with respect to the second component. Set $b(t)$ to be the delta function with mass at 0. Because $\alpha(0) = \tilde{\alpha}(0) = 1$, this yields

$$f'_2 \left\{ Y, \int_0^1 \alpha(t) a(t) dt \right\} = \tilde{f}'_2 \left\{ Y, \int_0^1 \tilde{\alpha}(t) a(t) dt \right\}$$

for any $a(\cdot)$, hence subsequently from (S3),

$$\int_0^1 \alpha(t) b(t) dt = \int_0^1 \tilde{\alpha}(t) b(t) dt$$

for any $b(\cdot)$. Because $\alpha(t), \tilde{\alpha}(t)$ are continuous, the latter directly yields $\alpha(t) = \tilde{\alpha}(t)$. From (S2), this further indicates $f(Y, \cdot) = \tilde{f}(Y, \cdot)$. It is now easy to see from (S1) that by taking $X_1(t), \dots, X_{j-1}(t), X_{j+1}(t), \dots, X_J(t)$ to be zero, we can obtain $\beta_j = \tilde{\beta}_j$ for $j = 1, \dots, J - 1$. This contradicts the assumption $\{f, \boldsymbol{\beta}, \alpha(t)\} \neq \{\tilde{f}, \tilde{\boldsymbol{\beta}}, \tilde{\alpha}(t)\}$. Hence the model in (1) is indeed identifiable. \square

S2.2 Proof of Proposition 2

Recall that we can write $\boldsymbol{\beta}^T \mathbf{Z}_i \boldsymbol{\gamma}$ as $\int_0^1 \mathbf{B}_r(t)^T \boldsymbol{\gamma} \boldsymbol{\beta}^T \mathbf{X}_i(t) dt$. Note that

$$E([\mathbf{S}_{\text{eff}\boldsymbol{\beta}}\{Y_i, \mathbf{X}_i(\cdot); \boldsymbol{\beta}_0, \alpha_0(\cdot), g^*\}^T, \mathbf{S}_{\text{eff}\boldsymbol{\gamma}}\{Y_i, \mathbf{X}_i(\cdot); \boldsymbol{\beta}_0, \alpha_0(\cdot), g^*\}^T]^T) = \mathbf{0},$$

where $[\mathbf{S}_{\text{eff}\boldsymbol{\beta}}\{Y_i, \mathbf{X}_i(\cdot); \boldsymbol{\beta}_0, \alpha_0(\cdot), g^*\}^T, \mathbf{S}_{\text{eff}\boldsymbol{\gamma}}\{Y_i, \mathbf{X}_i(\cdot); \boldsymbol{\beta}_0, \alpha_0(\cdot), g^*\}^T]^T$ is the vector which replaces the occurrence of $\mathbf{B}_r(\cdot)^T \boldsymbol{\gamma}$ in the vector $[\mathbf{S}_{\text{eff}\boldsymbol{\beta}}(Y_i, \mathbf{Z}_i, \boldsymbol{\beta}_0, \boldsymbol{\gamma}, g^*)^T, \mathbf{S}_{\text{eff}\boldsymbol{\gamma}}(Y_i, \mathbf{Z}_i, \boldsymbol{\beta}_0, \boldsymbol{\gamma}, g^*)^T]^T$ by $\alpha_0(\cdot)$. So the uniform convergence of $\mathbf{B}_r(\cdot)^T \boldsymbol{\gamma}_0$ to $\alpha_0(\cdot)$ leads to

$$E\{\mathbf{S}_{\text{eff}\boldsymbol{\beta}}(Y_i, \mathbf{Z}_i, \boldsymbol{\beta}_0, \boldsymbol{\gamma}_0, g^*)^T, \mathbf{S}_{\text{eff}\boldsymbol{\gamma}}(Y_i, \mathbf{Z}_i, \boldsymbol{\beta}_0, \boldsymbol{\gamma}_0, g^*)^T\}^T = o(1).$$

On the other hand, from the estimating equation

$$n^{-1} \sum_{i=1}^n \{\widehat{\mathbf{S}}_{\text{eff}\boldsymbol{\beta}}(Y_i, \mathbf{Z}_i, \widehat{\boldsymbol{\beta}}, \widehat{\boldsymbol{\gamma}}, g^*)^T, \widehat{\mathbf{S}}_{\text{eff}\boldsymbol{\gamma}}(Y_i, \mathbf{Z}_i, \widehat{\boldsymbol{\beta}}, \widehat{\boldsymbol{\gamma}}, g^*)^T\}^T = \mathbf{0},$$

using the consistency of the nonparametric kernel estimation, we have

$$n^{-1} \sum_{i=1}^n \{\mathbf{S}_{\text{eff}\boldsymbol{\beta}}(Y_i, \mathbf{Z}_i, \widehat{\boldsymbol{\beta}}, \widehat{\boldsymbol{\gamma}}, g^*)^T, \mathbf{S}_{\text{eff}\boldsymbol{\gamma}}(Y_i, \mathbf{Z}_i, \widehat{\boldsymbol{\beta}}, \widehat{\boldsymbol{\gamma}}, g^*)^T\}^T = o_p(1).$$

The law of large numbers further leads to

$$\begin{aligned} E\{\mathbf{S}_{\text{eff}\boldsymbol{\beta}}(Y_i, \mathbf{Z}_i, \boldsymbol{\beta}, \boldsymbol{\gamma}, g^*)^T, \\ \mathbf{S}_{\text{eff}\boldsymbol{\gamma}}(Y_i, \mathbf{Z}_i, \boldsymbol{\beta}, \boldsymbol{\gamma}, g^*)^T\}^T \Big|_{\boldsymbol{\beta}=\widehat{\boldsymbol{\beta}}, \boldsymbol{\gamma}=\widehat{\boldsymbol{\gamma}}} = o_p(1). \end{aligned} \tag{S4}$$

The unique root property in Condition (A7) implies that the derivative of

$$E[\{\mathbf{S}_{\text{eff}\boldsymbol{\beta}}(Y_i, \mathbf{Z}_i, \boldsymbol{\beta}, \boldsymbol{\gamma}, g^*)^T, (Y_i, \mathbf{Z}_i, \boldsymbol{\beta}, \boldsymbol{\gamma}, g^*)^T\}^T]$$

with respect to $(\boldsymbol{\beta}^T, \boldsymbol{\gamma}^T)^T$ is a nonsingular matrix in the neighborhood where the function value is $\mathbf{0}$. Therefore, the left hand side of both (S4) and (S4) are invertible functions of $(\boldsymbol{\beta}^T, \boldsymbol{\gamma}^T)^T$. This implies $\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0 = o_p(1)$ and $\widehat{\boldsymbol{\gamma}} - \boldsymbol{\gamma}_0 = o_p(1)$ by the continuous mapping theorem. \square

S2.3 Proof of Proposition 3

Denote the nuisance tangent space corresponding to f and the marginal density of \mathbf{Z} as respectively Λ_f and Λ_z . Taking derivative of the loglikelihood function with respect to the nuisance parameters in each parametric submodel and then taking the closure of their union, we have

$$\begin{aligned}\Lambda_z &= \{\mathbf{f}(\mathbf{Z}) : \forall \mathbf{f} \text{ such that } E(\mathbf{f}) = \mathbf{0}\} \\ \Lambda_f &= \{\mathbf{f}(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}) : \forall \mathbf{f} \text{ such that } E(\mathbf{f} | \mathbf{Z}) = E(\mathbf{f} | \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}) = \mathbf{0}\}.\end{aligned}$$

We can easily verify that $\Lambda_z \perp \Lambda_f$, hence $\Lambda = \Lambda_z \oplus \Lambda_f$, where Λ is the nuisance tangent space.

Thus, $\Lambda^\perp = \Lambda_z^\perp \cap \Lambda_f^\perp$. It is easy to see that $\Lambda_z^\perp = \{\mathbf{f}(Y, \mathbf{Z}) : E(\mathbf{f} | \mathbf{Z}) = 0\}$. We now show that $\Lambda_f^\perp = \{\mathbf{f}(Y, \mathbf{Z}) : E(\mathbf{f} | Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}) = E(\mathbf{f} | \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})\}$. We show this in two aspects. First, it is easy to verify that functions having the above conditional expectation property are elements in Λ_f^\perp . To show the second aspect that elements in Λ_f^\perp have to satisfy the conditional expectation requirement, consider any $\mathbf{f}(Y, \mathbf{Z}) \in \Lambda_f^\perp$. We choose $\mathbf{g} = E(\mathbf{f} | Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}) - E(\mathbf{f} | \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})$. Obviously, $\mathbf{g} \in \Lambda_f$ hence $E(\mathbf{g}^T \mathbf{f}) = 0$. We write this relation alternatively as

$$\begin{aligned}0 = E(\mathbf{g}^T \mathbf{f}) &= E\{\mathbf{g}^T E(\mathbf{f} | Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})\} \\ &= E(\mathbf{g}^T \mathbf{g}) + E\{\mathbf{g}^T E(\mathbf{f} | \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})\} \\ &= E(\mathbf{g}^T \mathbf{g}) + E\{E(\mathbf{g} | \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})^T E(\mathbf{f} | \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})\} \\ &= E(\mathbf{g}^T \mathbf{g}) + 0.\end{aligned}$$

This implies \mathbf{g} itself should be zero. This means \mathbf{f} indeed satisfies the conditional expectation requirement.

We are now ready to prove the form of Λ^\perp . For convenience, we denote set described in the proposition A first and we will establish $\Lambda^\perp = A$ through proving $\Lambda^\perp \subset A$ and $A \subset \Lambda^\perp$. To see $A \subset \Lambda^\perp$, we can verify that for any $\mathbf{f}(Y, \mathbf{Z}) - E(\mathbf{f} \mid Y, \boldsymbol{\beta}^\top \mathbf{Z} \boldsymbol{\gamma}) \in A$, we obviously have $E\{\mathbf{f}(Y, \mathbf{Z}) - E(\mathbf{f} \mid Y, \boldsymbol{\beta}^\top \mathbf{Z} \boldsymbol{\gamma}) \mid \mathbf{Z}\} = E(\mathbf{f} \mid \mathbf{Z}) - E(\mathbf{f} \mid \boldsymbol{\beta}^\top \mathbf{Z} \boldsymbol{\gamma}) = \mathbf{0}$, thus $A \subset \Lambda^\perp$. The form of elements in \mathbf{A} also ensures that $E\{\mathbf{f}(Y, \mathbf{Z}) - E(\mathbf{f} \mid Y, \boldsymbol{\beta}^\top \mathbf{Z} \boldsymbol{\gamma}) \mid Y, \boldsymbol{\beta}^\top \mathbf{Z} \boldsymbol{\gamma}\} = \mathbf{0} = E\{\mathbf{f}(Y, \mathbf{Z}) - E(\mathbf{f} \mid Y, \boldsymbol{\beta}^\top \mathbf{Z} \boldsymbol{\gamma}) \mid \boldsymbol{\beta}^\top \mathbf{Z} \boldsymbol{\gamma}\}$. Thus $A \subset \Lambda^\perp$. This shows $A \subset \Lambda^\perp$. We now show $\Lambda^\perp \subset A$. Assume $\mathbf{g}(Y, \mathbf{Z}) \in \Lambda^\perp$. Then $E(\mathbf{g} \mid \mathbf{Z}) = \mathbf{0}$ and $E(\mathbf{g} \mid Y, \boldsymbol{\beta}^\top \mathbf{Z} \boldsymbol{\gamma}) = E(\mathbf{g} \mid \boldsymbol{\beta}^\top \mathbf{Z} \boldsymbol{\gamma}) = E\{E(\mathbf{g} \mid \mathbf{Z}) \mid \boldsymbol{\beta}^\top \mathbf{Z} \boldsymbol{\gamma}\} = \mathbf{0}$. This means we can always write $\mathbf{g}(Y, \mathbf{Z})$ as $\mathbf{f}(Y, \mathbf{Z}) - E(\mathbf{f} \mid Y, \boldsymbol{\beta}^\top \mathbf{Z} \boldsymbol{\gamma})$. The additional requirement of $E(\mathbf{g} \mid \mathbf{Z}) = \mathbf{0}$ further imposes $E(\mathbf{f} \mid \mathbf{Z}) = E\{E(\mathbf{f} \mid Y, \boldsymbol{\beta}^\top \mathbf{Z} \boldsymbol{\gamma}) \mid \mathbf{Z}\} = E(\mathbf{f} \mid \boldsymbol{\beta}^\top \mathbf{Z} \boldsymbol{\gamma})$. Thus, we indeed have $\Lambda^\perp \subset A$. \square

S3 Proofs of the theorems in the main text

S3.1 Proof of Theorem 1

By the consistency shown in Proposition 2, we expand the score function as

$$\begin{aligned} \mathbf{0} &= n^{-1/2} \sum_{i=1}^n \left\{ g^* \{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)\} \right. & (S5) \\ &\quad \left. - \frac{\sum_{j=1}^J K_h \{\boldsymbol{\beta}_0^\top \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)\} g^* \{Y_j, \boldsymbol{\beta}_0^\top \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)\}}{\sum_{j=1}^J K_h \{\boldsymbol{\beta}_0^\top \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)\}} \right\} \\ &\quad \boldsymbol{\Theta}_\gamma \left\{ \mathbf{Z}_i - \frac{\sum_{j=1}^J K_h \{\boldsymbol{\beta}_0^\top \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)\} \mathbf{Z}_j}{\sum_{j=1}^J K_h \{\boldsymbol{\beta}_0^\top \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)\}} \right\}^\top \boldsymbol{\beta}_0 \\ &= \mathbf{R} + \mathbf{T} n^{1/2} \{\hat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\}, & (S6) \end{aligned}$$

where

$$\begin{aligned} \mathbf{R} &= n^{-1/2} \sum_{i=1}^n \left\{ g^* (Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0) - \frac{\sum_{j=1}^J K_h (\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma}_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0) g^* (Y_j, \boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma}_0)}{\sum_{j=1}^J K_h (\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma}_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0)} \right\} \\ &\quad \times \boldsymbol{\Theta}_\gamma \left\{ \mathbf{Z}_i - \frac{\sum_{j=1}^J K_h (\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma}_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0) \mathbf{Z}_j}{\sum_{j=1}^J K_h (\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma}_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0)} \right\}^\top \boldsymbol{\beta}_0, \end{aligned}$$

$$\begin{aligned} \mathbf{T} &= n^{-1} \sum_{i=1}^n \partial \left[\left\{ g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma) - \frac{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma - \beta_0^\top \mathbf{Z}_i \gamma) g^*(Y_j, \beta_0^\top \mathbf{Z}_j \gamma)}{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma - \beta_0^\top \mathbf{Z}_i \gamma)} \right\} \right. \\ &\quad \left. \times \Theta_\gamma \left\{ \mathbf{Z}_i - \frac{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma - \beta_0^\top \mathbf{Z}_i \gamma) \mathbf{Z}_j}{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma - \beta_0^\top \mathbf{Z}_i \gamma)} \right\}^\top \beta_0 \right] / \partial(\beta_0^\top \mathbf{Z}_i \gamma) \Big|_{\gamma=\gamma^*} \beta_0^\top \mathbf{Z}_i \Theta_\gamma^\top, \end{aligned}$$

and γ^* is the point on the line connecting $\hat{\gamma}(\beta_0)$ and γ_0 .

The Asymptotic Property of \mathbf{R} Now \mathbf{R} can be written as $\mathbf{R} = \mathbf{R}_0 + \mathbf{R}_1 + \mathbf{R}_2 + \mathbf{R}_3$, where

$$\begin{aligned} \mathbf{R}_0 &= n^{-1/2} \sum_{i=1}^n [g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\gamma \\ &\quad \times \{\mathbf{Z}_i - E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0)\}^\top \beta_0, \\ \mathbf{R}_1 &= n^{-1/2} \sum_{i=1}^n [g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\gamma \\ &\quad \times \left\{ E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0) - \frac{\sum_{j=1}^J K_h\{\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0\} \mathbf{Z}_j}{\sum_{j=1}^J K_h\{\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0\}} \right\}^\top \beta_0, \\ \mathbf{R}_2 &= n^{-1/2} \sum_{i=1}^n \left[E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\} \right. \\ &\quad \left. - \frac{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) g^*(Y_j, \beta_0^\top \mathbf{Z}_j \gamma_0)}{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0)} \right] \Theta_\gamma \\ &\quad \times \{\mathbf{Z}_i - E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0)\}^\top \beta_0, \\ \mathbf{R}_3 &= n^{-1/2} \sum_{i=1}^n \left[E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\} \right. \\ &\quad \left. - \frac{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) g^*(Y_j, \beta_0^\top \mathbf{Z}_j \gamma_0)}{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0)} \right] \Theta_\gamma \\ &\quad \times \left\{ E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0) - \frac{\sum_{j=1}^J K_h\{\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0\} \mathbf{Z}_j}{\sum_{j=1}^J K_h\{\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0\}} \right\}^\top \beta_0. \end{aligned}$$

Further, we write $\mathbf{R}_1 = \mathbf{R}_{11} + \mathbf{R}_{12}$, where

$$\begin{aligned} \mathbf{R}_{11} &= n^{-1/2} \sum_{i=1}^n [g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\gamma \\ &\quad \times \left\{ \frac{E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0) \sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0)}{n f_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)} \right\}^\top \beta_0 \end{aligned}$$

$$\begin{aligned}
& \left. \frac{\sum_{j=1}^J K_h\{\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0\} \mathbf{Z}_j}{nf_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)} \right\}^\top \beta_0, \\
\mathbf{R}_{12} &= n^{-1/2} \sum_{i=1}^n [g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\gamma \\
& \times \left\{ \frac{E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0) \sum_{j=1}^J K_h\{\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0\}}{nf_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)} \right. \\
& \left. - \frac{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) \mathbf{Z}_j}{nf_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)} \right\}^\top \beta_0 \\
& \times \left\{ \frac{nf_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)}{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0)} - 1 \right\} \\
& = \mathbf{R}_{11} \left\{ \frac{nf_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)}{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0)} - 1 \right\},
\end{aligned}$$

where $f_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)$ is the density for $\beta_0^\top \mathbf{Z}_i \gamma_0$.

We first analyze \mathbf{R}_{11} . Using the U statistics property, we write \mathbf{R}_{11} as $\mathbf{R}_{11} = \mathbf{R}_{111} + \mathbf{R}_{112} - \mathbf{R}_{113} + o_p(\mathbf{R}_{111} + \mathbf{R}_{112} - \mathbf{R}_{113})$, where

$$\begin{aligned}
& \mathbf{R}_{11} \\
& = n^{-3/2} \sum_{i=1}^n \sum_{j=1}^J [g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\gamma \\
& \times \left\{ \frac{E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0) K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0)}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \gamma_0\}} \right. \\
& \left. - \frac{K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) \mathbf{Z}_j}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \gamma_0\}} \right\}^\top \beta_0 \\
& = \mathbf{R}_{111} + \mathbf{R}_{112} - \mathbf{R}_{113} + o_p(\mathbf{R}_{111} + \mathbf{R}_{112} - \mathbf{R}_{113}),
\end{aligned}$$

where

$$\begin{aligned}
\mathbf{R}_{111} &= \left\{ n^{-1/2} \sum_{i=1}^n E \left([g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\gamma \right. \right. \\
& \times \left\{ \frac{E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0) K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0)}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \gamma_0\}} \right. \\
& \left. \left. - \frac{K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) \mathbf{Z}_j}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \gamma_0\}} \right\}^\top \beta_0 | \mathbf{O}_i \right), \\
\mathbf{R}_{112} &= n^{-1/2} \sum_{j=1}^J E \left([g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\gamma \right.
\end{aligned}$$

$$\begin{aligned}
& \times \left\{ \frac{E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0) K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0)}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \gamma_0\}} \right. \\
& \left. - \frac{K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) \mathbf{Z}_j}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \gamma_0\}} \right\}^\top \beta_0 | \mathbf{O}_j), \\
\mathbf{R}_{113} &= n^{1/2} E \left([g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\gamma \right. \\
& \times \left\{ \frac{E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0) K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0)}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \gamma_0\}} \right. \\
& \left. - \frac{K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) \mathbf{Z}_j}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \gamma_0\}} \right\}^\top \beta_0 \Bigg),
\end{aligned}$$

where \mathbf{O}_i is the random variable corresponding to the i th observation. Now because the summand for \mathbf{R}_{111} , i.e.,

$$\begin{aligned}
& E \left([g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\gamma \right. \\
& \times \left\{ \frac{E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0) K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0)}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \gamma_0\}} \right. \\
& \left. - \frac{K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) \mathbf{Z}_j}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \gamma_0\}} \right\}^\top \beta_0 | \mathbf{O}_i) \\
&= [g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\gamma \\
& \times \left[\frac{E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0) E\{K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) | \mathbf{O}_i\}}{f_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)} \right. \\
& \left. - \frac{E\{K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) \mathbf{Z}_j | \mathbf{O}_i\}}{f_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)} \right]^\top \beta_0 \\
&= [g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\gamma \\
& \times \left[\frac{E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0) E\{K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) | \mathbf{O}_i\}}{f_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)} \right. \\
& \left. - \frac{E[K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) E(\mathbf{Z}_j | \beta_0^\top \mathbf{Z}_j \gamma_0) | \mathbf{O}_i]}{f_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)} \right]^\top \beta_0 \\
&= [g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\gamma \\
& \times \left[E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0)^\top \beta_0 \left\{ 1 + \int \frac{K(s) s^2}{2f_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)} \right. \right. \\
& \times \frac{\partial^2 f_{\mathbf{Z}}\{a(\beta_0^\top \mathbf{Z}_i \gamma_0, sh)\}}{\partial a(\beta_0^\top \mathbf{Z}_i \gamma_0, sh)^2} dsh^2 \Bigg\} - E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0)^\top \beta_0 - \int \frac{s^2 K(s)}{2f_{\mathbf{Z}}(\beta_0^\top \mathbf{Z}_i \gamma_0)} \\
& \times \frac{\partial^2 [E\{\mathbf{Z}_i | \beta_0^\top b(\beta_0^\top \mathbf{Z}_i \gamma_0, sh)\}^\top \beta_0 f_{\mathbf{Z}}\{b(\beta_0^\top \mathbf{Z}_i \gamma_0, sh)\}]}{\partial b(\beta_0^\top \mathbf{Z}_i \gamma_0, sh)^2} dsh^2 \Bigg]
\end{aligned}$$

$$\begin{aligned}
&= [g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0) | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\}] \boldsymbol{\Theta}_\gamma \\
&\quad \times \left[E(\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0)^\top \boldsymbol{\beta}_0 \int \frac{\partial^2 f_{\mathbf{Z}}\{a(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)\}}{\partial a(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)^2} \frac{s^2 K(s)}{2f_{\mathbf{Z}}(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0)} ds \right. \\
&\quad \left. - \int \frac{\partial^2 [E\{\mathbf{Z}_i | b(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)\}^\top \boldsymbol{\beta}_0 f_{\mathbf{Z}}\{b(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)\}]}{\partial b(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)^2} \frac{s^2 K(s)}{2f_{\mathbf{Z}}(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0)} ds \right] h^2, \tag{S7}
\end{aligned}$$

where $a(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh), b(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)$ are points on the line connecting $\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0$ and $\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0 + sh$. Note that $a(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh), b(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)$ depend on the values of both $\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0$ and sh and will go to $\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0$ when $h \rightarrow 0$. Now note that

$$\begin{aligned}
&[g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0) | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\}] \boldsymbol{\Theta}_\gamma \\
&\quad \times \left[E(\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0)^\top \boldsymbol{\beta}_0 \int \frac{\partial^2 f_{\mathbf{Z}}\{a(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)\}}{\partial a(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)^2} \frac{s^2 K(s)}{2f_{\mathbf{Z}}(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0)} ds \right. \\
&\quad \left. - \int \frac{\partial^2 [E\{\mathbf{Z}_i | b(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)\}^\top \boldsymbol{\beta}_0 f_{\mathbf{Z}}\{b(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)\}]}{\partial b(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)^2} \frac{s^2 K(s)}{2f_{\mathbf{Z}}(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0)} ds \right]
\end{aligned}$$

can be written as

$$\int_0^1 C_{1i}(t) \boldsymbol{\Theta}_\gamma \mathbf{B}_r(t) dt = \int_0^1 C_{1i}(t) \{B_{rk}(t), k = 2, \dots, d_\gamma\}^\top dt,$$

with

$$\begin{aligned}
&C_{1i}(t) \\
&= [g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0) | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\}] \\
&\quad \times \left[E(\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0) \int \frac{\partial^2 f_{\mathbf{Z}}\{a(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)\}}{\partial a(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)^2} \frac{s^2 K(s)}{2f_{\mathbf{Z}}(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0)} ds \right. \\
&\quad \left. - \int \frac{\partial^2 [E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | b(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)\} f_{\mathbf{Z}}\{b(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)\}]}{\partial b(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0, sh)^2} \frac{s^2 K(s)}{2f_{\mathbf{Z}}(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0)} ds \right].
\end{aligned}$$

Obviously $E\{C_{1i}(t)\} = 0$ and hence $|E\{C_{1i}(t)\}| < \infty$. From Conditions (A6) and (A8), $\|C_{1i}(\cdot)\|_2 < \infty$, *a.s.*, so by Lemma 3, we have

$$\|\mathbf{R}_{111}\|_\infty = O_p\{h^2 \sqrt{h_b \log(n)}\}, \tag{S8}$$

which also implies

$$\|\mathbf{R}_{113}\|_\infty = \|E(\mathbf{R}_{111})\|_\infty = O\{h^2 \sqrt{h_b \log(n)}\}. \tag{S9}$$

Further, the summand of \mathbf{R}_{112} , i.e.,

$$\begin{aligned}
& E \left([g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\}] \boldsymbol{\Theta}_\gamma \right. \\
& \times \left\{ \frac{E(\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) K_h(\boldsymbol{\beta}_0^\top \mathbf{Z}_j \gamma_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0)}{n f_{\mathbf{Z}}\{\boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\}} \right. \\
& \left. \left. - \frac{K_h(\boldsymbol{\beta}_0^\top \mathbf{Z}_j \gamma_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) \mathbf{Z}_j}{n f_{\mathbf{Z}}\{\boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\}} \right\}^\top \boldsymbol{\beta}_0 | \mathbf{O}_j \right) \\
& = E \left(E \left([g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\}] | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0, \mathbf{O}_j \right) \boldsymbol{\Theta}_\gamma \right. \\
& \times \left\{ \frac{E(\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) K_h(\boldsymbol{\beta}_0^\top \mathbf{Z}_j \gamma_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0)}{n f_{\mathbf{Z}}\{\boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\}} \right. \\
& \left. \left. - \frac{K_h(\boldsymbol{\beta}_0^\top \mathbf{Z}_j \gamma_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) \mathbf{Z}_j}{n f_{\mathbf{Z}}\{\boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\}} \right\}^\top \boldsymbol{\beta}_0 | \mathbf{O}_j \right) \\
& = \mathbf{0}.
\end{aligned} \tag{S10}$$

Combining (S8), (S10), (S9), we get

$$\mathbf{R}_{11} = O_p\{h^2 \sqrt{h_b \log(n)}\}. \tag{S11}$$

Further, to treat \mathbf{R}_{12} , note that

$$\begin{aligned}
& \left\{ \frac{n f_{\mathbf{Z}}(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0)}{\sum_{j=1}^J K_h(\boldsymbol{\beta}_0^\top \mathbf{Z}_j \gamma_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0)} - 1 \right\} \\
& = \left\{ \frac{f_{\mathbf{Z}}(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) - n^{-1} \sum_{j=1}^J K_h(\boldsymbol{\beta}_0^\top \mathbf{Z}_j \gamma_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0)}{n^{-1} \sum_{j=1}^J K_h(\boldsymbol{\beta}_0^\top \mathbf{Z}_j \gamma_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0)} \right\} \\
& = O_p\{h^2 + (nh)^{-1/2}\}
\end{aligned} \tag{S12}$$

hence

$$\|\mathbf{R}_{12}\|_\infty = o_p\{h^2 \sqrt{h_b \log(n)}\}. \tag{S13}$$

Thus, combining (S11) and (S13), we have

$$\|\mathbf{R}_1\|_\infty = O_p\{h^2 \sqrt{h_b \log(n)}\}. \tag{S14}$$

Using similar derivation as those led to (S14) while exchange the roles of \mathbf{Z} and g^* , we can obtain

$$\|\mathbf{R}_2\|_\infty = O_p\{h^2\sqrt{h_b\log(n)}\}. \quad (\text{S15})$$

For \mathbf{R}_3 , we first note that

$$\begin{aligned} & \left| \left[E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\} - \frac{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) g^*(Y_j, \beta_0^\top \mathbf{Z}_j \gamma_0)}{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0)} \right] \right| \\ &= O_p(h^2 + n^{-1/2} h^{-1/2}) \end{aligned}$$

by the uniform consistency of the kernel estimator. Further, the summand in \mathbf{R}_3 has the form

$$\begin{aligned} & \left[E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\} - \frac{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) g^*(Y_j, \beta_0^\top \mathbf{Z}_j \gamma_0)}{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0)} \right] \Theta_\gamma \\ & \times \left\{ E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0) - \frac{\sum_{j=1}^J K_h\{\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0\} \mathbf{Z}_j}{\sum_{j=1}^J K_h\{\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0\}} \right\}^\top \beta_0 \\ &= \int_0^1 (h^4 + n^{-1} h^{-1}) C_{2i}(t) \Theta_\gamma \mathbf{B}_r(t) dt \\ &= \int_0^1 (h^4 + n^{-1} h^{-1}) C_{2i}(t) \{B_{rk}(t), k = 2, \dots, d_\gamma\}^\top dt, \end{aligned}$$

where

$$\begin{aligned} & C_{2i}(t) \\ &= (h^4 + n^{-1} h^{-1})^{-1} \left[E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\} \right. \\ & \quad \left. - \frac{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0) g^*(Y_j, \beta_0^\top \mathbf{Z}_j \gamma_0)}{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0)} \right] \\ & \quad \times \left\{ E\{\mathbf{X}_i(t)^\top \beta_0 | \beta_0^\top \mathbf{Z}_i \gamma_0\} - \frac{\sum_{j=1}^J K_h\{\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0\} \mathbf{X}_j(t)^\top \beta_0}{\sum_{j=1}^J K_h\{\beta_0^\top \mathbf{Z}_j \gamma_0 - \beta_0^\top \mathbf{Z}_i \gamma_0\}} \right\}. \end{aligned}$$

Note that $E\{C_{2i}(t)\} \neq 0$, $|E\{C_{2i}(t)\}| < \infty$, $\|C_{2i}(\cdot)\|_2 < \infty$, *a.s.* by Conditions (A2), (A6) and the uniform consistency of the kernel estimator. So by Lemma 3, we have

$$\mathbf{R}_3 = n^{-1/2} \sum_{i=1}^n \int_0^1 (h^4 + n^{-1} h^{-1}) C_{2i}\{B_{rk}(t), k = 2, \dots, d_\gamma\}^\top dt$$

$$= O_p\{(n^{1/2}h^4 + n^{-1/2}h^{-1})h_b\}. \quad (\text{S16})$$

We now assess (S7). We write

$$\begin{aligned} \mathbf{R}_0 &= n^{-1/2} \sum_{i=1}^n [g^*\{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\} - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\}] \boldsymbol{\Theta}_\gamma \\ &\quad \times \{\mathbf{Z}_i - E(\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0)\}^\top \boldsymbol{\beta}_0 \\ &= n^{-1/2} \sum_{i=1}^n \int_0^1 C_{3i}(t) \boldsymbol{\Theta}_\gamma \mathbf{B}_r(t) dt \\ &= n^{-1/2} \sum_{i=1}^n \int_0^1 C_{3i}(t) \{B_{rk}(t), k = 2, \dots, d_\gamma\}^\top dt, \end{aligned}$$

where

$$\begin{aligned} C_{3i}(t) &= [g^*\{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\} - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\}] [\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 \\ &\quad - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\}]. \end{aligned}$$

We can easily verify that $E\{C_{3i}(t)\} \neq 0$, $E\{C_{3i}(t)\} < \infty$ and $\|C_{3i}(\cdot)\|_2 < \infty$, *a.s.* by Condition (A6). Therefore, by Lemma 3 we know

$$\|\mathbf{R}_0\|_\infty = O_p(n^{1/2}h_b). \quad (\text{S17})$$

Comparing (S14), (S15), (S16) with (S17), from Condition (A2), it is clear that \mathbf{R}_0 dominates $\mathbf{R}_1, \mathbf{R}_2$ and \mathbf{R}_3 . We further analyze \mathbf{R}_0 by writing

$$\mathbf{R}_0 = \mathbf{R}_{00} + \mathbf{R}_{01} + \mathbf{R}_{02} \quad (\text{S18})$$

where

$$\begin{aligned} \mathbf{R}_{00} &= n^{-1/2} \sum_{i=1}^n [g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \boldsymbol{\Theta}_\gamma \\ &\quad \times [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]^\top \boldsymbol{\beta}_0 \end{aligned} \quad (\text{S19})$$

and

$$\mathbf{R}_{01} = n^{-1/2} \sum_{i=1}^n \left([g^*\{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\} | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\}] \right)$$

$$\begin{aligned}
& -[g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \boldsymbol{\Theta}_\gamma \\
& \times [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0\}]^T \boldsymbol{\beta}_0,
\end{aligned}$$

$$\begin{aligned}
\mathbf{R}_{02} &= n^{-1/2} \sum_{i=1}^n [g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \boldsymbol{\Theta}_\gamma \\
& \times \left([\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0\}] - [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right)^T \boldsymbol{\beta}_0.
\end{aligned}$$

To analyze \mathbf{R}_{00} , we write it as

$$\begin{aligned}
\mathbf{R}_{00} &= n^{-1/2} \sum_{i=1}^n \int_0^1 C_{4i}(t) \boldsymbol{\Theta}_\gamma \mathbf{B}_r(t) dt \\
&= n^{-1/2} \sum_{i=1}^n \int_0^1 C_{4i}(t) \{B_{rk}(t), k = 2, \dots, d_\gamma\}^T dt,
\end{aligned}$$

where

$$\begin{aligned}
& C_{4i}(t) \\
&= [g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] [\mathbf{X}_i(t)^T \boldsymbol{\beta}_0 \\
& \quad - E\{\mathbf{X}_i(t)^T \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}].
\end{aligned}$$

We can check that $E\{C_{4i}(t)\} = 0$ and $\|C_{4i}(\cdot)\|_2 < \infty$ *a.s.* by Condition (A6). Thus, by Lemma 3,

$$\|\mathbf{R}_{00}\|_\infty = \sqrt{h_b \log(n)}. \tag{S20}$$

Further

$$\begin{aligned}
\mathbf{R}_{02} &= n^{-1/2} \sum_{i=1}^n \int_0^1 h_b^q C_{5i}(t) \boldsymbol{\Theta}_\gamma \mathbf{B}_r(t) dt \\
&= n^{-1/2} \sum_{i=1}^n \int_0^1 h_b^q C_{5i}(t) \{B_{rk}(t), k = 2, \dots, d_\gamma\}^T dt,
\end{aligned}$$

where

$$C_{5i}(t) = h_b^{-q} [g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]$$

$$\begin{aligned} & \times \left([\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\}] - [\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 \right. \\ & \left. - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right). \end{aligned}$$

Now $E\{C_{5i}(t)\} = 0$ because

$$\begin{aligned} & E \left\{ [g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right. \\ & \times \left([\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\}] - [\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 \right. \\ & \left. \left. - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right) \right\} \\ & = E \left[E \left\{ [g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] | \mathbf{X}_i \right\} \right. \\ & \times \left([\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\}] - [\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 \right. \\ & \left. \left. - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right) \right] \\ & = 0. \end{aligned}$$

Further $\|C_{5i}(\cdot)\|_2 < \infty$, *a.s.* by Condition (A6). Therefore, by Lemma 3 we have

$$\begin{aligned} & \|\mathbf{R}_{02}\|_\infty \\ & = \|n^{-1/2} \sum_{i=1}^n [g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \boldsymbol{\Theta}_\gamma \\ & \quad \times \left([\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\}] - [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right)^\top \boldsymbol{\beta}_0\|_\infty \\ & = O_p\{h_b^q \sqrt{h_b} \log(n)\}. \end{aligned}$$

In addition,

$$\begin{aligned} \mathbf{R}_{01} & = n^{-1/2} \sum_{i=1}^n \int_0^1 h_b^q C_{6i}(t) \boldsymbol{\Theta}_\gamma \mathbf{B}_r(t) dt \\ & = n^{-1/2} \sum_{i=1}^n \int_0^1 h_b^q C_{6i}(t) \{B_{rk}(t), k = 2, \dots, d_\gamma\}^\top dt, \end{aligned}$$

where

$$C_{6i}(t) = h_b^{-q} \left([g^*\{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\} | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\}] \right)$$

$$\begin{aligned}
& -[g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\} | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \\
& \times [\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\}],
\end{aligned}$$

with $E\{C_{6i}(t)\} \neq 0$, $|E\{C_{6i}(t)\}| < \infty$, $\|C_{6i}(\cdot)\|_2 < \infty$, *a.s.* by Condition (A6). Therefore, by Lemma 3 we have

$$\begin{aligned}
\|\mathbf{R}_{01}\|_\infty &= \|n^{-1/2} \sum_{i=1}^n \left([g^*\{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\} | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\}] \right. \\
& \quad \left. - [g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\} | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right) \boldsymbol{\Theta}_\gamma \\
& \quad \times [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\}]^\top \boldsymbol{\beta}_0 \|_\infty \\
&= O_p(h_b^{q+1} n^{1/2}).
\end{aligned}$$

Now by the fact that $\mathbf{R}_{01} + \mathbf{R}_{02} = O_p\{h_b^{q+1} n^{1/2} + h_b^q \sqrt{h_b \log(n)}\}$ and $\|\mathbf{R}_{00}\| = O_p\{\sqrt{h_b \log(n)}\}$ by (S20), we have $\mathbf{R}_{01} + \mathbf{R}_{02} = o_p(\mathbf{R}_{00})$ by Condition (A4). Therefore, by (S18) we have $\mathbf{R}_0 = \mathbf{R}_{00} + o_p(\mathbf{R}_{00})$, combining with the fact that \mathbf{R}_0 dominates $\mathbf{R}_1, \mathbf{R}_2, \mathbf{R}_3$ and $\mathbf{R} = \mathbf{R}_0 + \mathbf{R}_1 + \mathbf{R}_2 + \mathbf{R}_3$ in (S5), we have

$$\mathbf{R} = \mathbf{R}_{00} + o_p(\mathbf{R}_{00}), \quad (\text{S21})$$

i.e.,

$$\begin{aligned}
& n^{-1/2} \sum_{i=1}^n \left\{ g^*\{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\} - \frac{\sum_{j=1}^J K_h\{\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma}_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\} g^*\{Y_j, \boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma}_0\}}{\sum_{j=1}^J K_h\{\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma}_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\}} \right\} \\
& \times \boldsymbol{\Theta}_\gamma \left\{ \mathbf{Z}_i - \frac{\sum_{j=1}^J K_h\{\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma}_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\} \mathbf{Z}_j}{\sum_{j=1}^J K_h\{\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma}_0 - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}_0\}} \right\}^\top \boldsymbol{\beta}_0 = \mathbf{R}_{00} + o_p(\mathbf{R}_{00}),
\end{aligned}$$

where \mathbf{R}_{00} is given in (S19).

The Asymptotic Property of \mathbf{T} Now consider the term

$$\begin{aligned}
\mathbf{T} &= \left(n^{-1} \sum_{i=1}^n \partial \left[\left\{ g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}) \right. \right. \right. \\
& \quad \left. \left. - \frac{\sum_{j=1}^J K_h(\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma} - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}) g^*(Y_j, \boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma})}{\sum_{j=1}^J K_h(\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma} - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma})} \right\} \right]
\end{aligned}$$

$$\begin{aligned}
& \times \Theta_\gamma \left\{ \mathbf{Z}_i - \frac{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma - \beta_0^\top \mathbf{Z}_i \gamma) \mathbf{Z}_j}{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma - \beta_0^\top \mathbf{Z}_i \gamma)} \right\}^\top \beta_0 \Bigg|_{\gamma=\gamma^*} \\
& / \partial(\beta_0^\top \mathbf{Z}_i \gamma) \Big|_{\gamma=\gamma^*} \beta_0^\top \mathbf{Z}_i \Theta_\gamma^\top \Bigg|_{\gamma=\gamma^*}
\end{aligned} \tag{S22}$$

in (S5). We decompose \mathbf{T} as

$$\mathbf{T} = \mathbf{T}_0 + \mathbf{T}_1 + \mathbf{T}_2,$$

where

$$\begin{aligned}
\mathbf{T}_0 &= \left\{ n^{-1} \sum_{i=1}^n \partial \left([g^*(Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)) - E\{g^*(Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)) | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma \right. \right. \\
& \quad \left. \left. \times [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}]^\top \beta_0 \right) / \partial\{\beta_0^\top \alpha_0(\mathbf{X}_i)\} \beta_0^\top \mathbf{Z}_i \Theta_\gamma^\top \right\}, \\
\mathbf{T}_1 &= \left\{ n^{-1} \sum_{i=1}^n \partial \left([g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma) | \beta_0^\top \mathbf{Z}_i \gamma\}] \Theta_\gamma \right. \right. \\
& \quad \left. \left. \times [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma\}]^\top \beta_0 \right) / \partial(\beta_0^\top \mathbf{Z}_i \gamma) \Big|_{\gamma=\gamma^*} \beta_0^\top \mathbf{Z}_i \Theta_\gamma^\top \right\} \\
& \quad - \left\{ n^{-1} \sum_{i=1}^n \partial \left([g^*(Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)) - E\{g^*(Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)) | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma \right. \right. \\
& \quad \left. \left. \times [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}]^\top \beta_0 \right) / \partial\{\beta_0^\top \alpha_0(\mathbf{X}_i)\} \beta_0^\top \mathbf{Z}_i \Theta_\gamma^\top \right\}, \\
\mathbf{T}_2 &= \left(n^{-1} \sum_{i=1}^n \partial \left[\left\{ g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma) - \frac{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma - \beta_0^\top \mathbf{Z}_i \gamma) g^*(Y_j, \beta_0^\top \mathbf{Z}_j \gamma)}{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma - \beta_0^\top \mathbf{Z}_i \gamma)} \right\} \right. \right. \\
& \quad \left. \left. \times \Theta_\gamma \left\{ \mathbf{Z}_i - \frac{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma - \beta_0^\top \mathbf{Z}_i \gamma) \mathbf{Z}_j}{\sum_{j=1}^J K_h(\beta_0^\top \mathbf{Z}_j \gamma - \beta_0^\top \mathbf{Z}_i \gamma)} \right\}^\top \beta_0 \right] / \partial(\beta_0^\top \mathbf{Z}_i \gamma) \Big|_{\gamma=\gamma^*} \beta_0^\top \mathbf{Z}_i \Theta_\gamma^\top \right) \\
& \quad - \left\{ n^{-1} \sum_{i=1}^n \partial \left([g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma) | \beta_0^\top \mathbf{Z}_i \gamma\}] \Theta_\gamma \right. \right. \\
& \quad \left. \left. \times [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma\}]^\top \beta_0 \right) / \partial(\beta_0^\top \mathbf{Z}_i \gamma) \Big|_{\gamma=\gamma^*} \beta_0^\top \mathbf{Z}_i \Theta_\gamma^\top \right\}.
\end{aligned}$$

Now

$$\|\mathbf{T}_0\|_\infty = \max_{k=1, \dots, d_\gamma} \sum_{l=1}^{d_\gamma} \left| n^{-1} \sum_{i=1}^n \left[\int_0^1 \tilde{C}_{\tau_i}(t) \{B_{rk}(t)\} dt \right. \right.$$

$$\begin{aligned}
& \times \int_0^1 \boldsymbol{\beta}_0^T \mathbf{X}_i(s) \{B_{rl}(s) - B_{rl}(0)/B_{r1}(0)B_{r1}(s)\} ds \Big| \Big| \\
= & \max_{k=1, \dots, d_\gamma} \sum_{l=1}^{d_\gamma} \left| n^{-1} \sum_{i=1}^n \left[\int_0^1 \tilde{C}_{7i}(t) \{B_{rk}(t)\} dt \right. \right. \\
& \left. \left. \times \boldsymbol{\beta}_0^T \mathbf{X}_i(\xi_1) \{B_{rl}(\xi_1) - B_{rl}(0)/B_{r1}(0)B_{r1}(\xi_1)\} \right] \right| \\
= & \max_{k=1, \dots, d_\gamma} \left| n^{-1} \sum_{i=1}^n \left[\int_0^1 \tilde{C}_{7i}(t) \{B_{rk}(t)\} dt \right. \right. \\
& \left. \left. \times \boldsymbol{\beta}_0^T \mathbf{X}_i(\xi_1) \right] \right| \left| \sum_{l=1}^{d_\gamma} \{B_{rl}(\xi_1) - B_{rl}(0)/B_{r1}(0)B_{r1}(\xi_1)\} \right| \\
= & \max_{k=1, \dots, d_\gamma} \left| n^{-1} \sum_{i=1}^n \int_0^1 \tilde{C}_{7i}(t) \{B_{rk}(t)\} dt \right. \\
& \left. \times \boldsymbol{\beta}_0^T \mathbf{X}_i(\xi_1) \right| M \\
= & \max_{k=1, \dots, d_\gamma} \left| n^{-1} \sum_{i=1}^n \int_0^1 a_n C_{7i}(t) \{B_{rk}(t)\} dt \right|,
\end{aligned}$$

where ξ_1 is a point in $(0, 1)$, and

$$\begin{aligned}
M &= \sum_{l=1}^{d_\gamma} \left| \{B_{rl}(\xi_1) - B_{rl}(0)/B_{r1}(0)B_{r1}(\xi_1)\} \right| \\
&\leq \sum_{l=1}^{d_\gamma} B_{rl}(\xi_1) + \sum_{l=1}^{d_\gamma} B_{rl}(0)/B_{r1}(0)B_{r1}(\xi_1) \\
&< \infty,
\end{aligned}$$

which holds by (3.4) on page 141 in DeVore and Lorentz (1993), and a_n is the sequence such that $\boldsymbol{\beta}_0^T \mathbf{X}_i(\xi_1) = O_{a.s.}(a_n)$. Note that a_n does not need to be bounded. Here

$$\begin{aligned}
\tilde{C}_{7i}(t) &= \partial \left([g^*(Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)) - E\{g^*(Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)) | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right. \\
&\quad \left. \times [\mathbf{X}_i(t)^T \boldsymbol{\beta}_0 - E\{\mathbf{X}_i(t)^T \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]^T \boldsymbol{\beta}_0 \right) / \partial \{\boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}
\end{aligned}$$

and

$$C_{7i}(t) = a_n^{-1} \partial \left([g^*(Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)) - E\{g^*(Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)) | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right)$$

$$\begin{aligned} & \times [\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]^\top \boldsymbol{\beta}_0) / \partial\{\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \\ & \times M\boldsymbol{\beta}_0^\top \mathbf{X}_i(\xi_1). \end{aligned}$$

Now $E\{C_{7i}(t)\} \neq 0$, $|E\{C_{7i}(t)\}| < \infty$, and $\|C_{7i}(\cdot)\|_2 < \infty$. By Lemma 3, we have $\|\mathbf{T}_0\|_\infty = O_p(h_b a_n)$. Similarly,

$$\|\mathbf{T}_1\|_\infty = \max_{k=1, \dots, d_\gamma} |n^{-1} \sum_{i=1}^n \int_0^1 h_b^q a_n C_{8i}(t) \{B_{rk}(t)\} dt|$$

where

$$\begin{aligned} C_{8i}(t) &= h_b^{-q} a_n^{-1} \left\{ \partial \left([g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}) | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}\}] \right. \right. \\ & \quad \times [\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}\}] \left. \right) / \partial(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}) \Big|_{\boldsymbol{\gamma}=\boldsymbol{\gamma}^*} M\boldsymbol{\beta}_0^\top \mathbf{X}_i(\xi_1) \\ & \quad - \partial \left([g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right. \\ & \quad \times [\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \left. \right) / \partial\{\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} M\boldsymbol{\beta}_0^\top \mathbf{X}_i(\xi_1) \left. \right\}, \end{aligned}$$

with $E\{C_{8i}(t)\} \neq 0$, $E\{C_{8i}(t)\} < \infty$, and $\|C_{8i}(\cdot)\|_2 < \infty$. By Lemma 3, we have $\|\mathbf{T}_1\|_\infty = O_p(h_b^{q+1} a_n)$. Next,

$$\|\mathbf{T}_2\|_\infty = \max_{k=1, \dots, d_\gamma} |n^{-1} \sum_{i=1}^n \int_0^1 a_n (h^2 + n^{-1/2} h^{-1/2}) C_{9i}(t) \{B_{rk}(t)\} dt|,$$

where

$$\begin{aligned} C_{9i}(t) &= a_n^{-1} (h^2 + n^{-1/2} h^{-1/2})^{-1} \left(\partial \left[\left\{ g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}) \right. \right. \right. \\ & \quad \left. \left. \left. - \frac{\sum_{j=1}^J K_h(\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma} - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}) g^*(Y_j, \boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma})}{\sum_{j=1}^J K_h(\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma} - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma})} \right\} \right. \right. \\ & \quad \left. \left. \times \left\{ \mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 - \frac{\sum_{j=1}^J K_h(\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma} - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}) \mathbf{X}_j(t)^\top \boldsymbol{\beta}_0}{\sum_{j=1}^J K_h(\boldsymbol{\beta}_0^\top \mathbf{Z}_j \boldsymbol{\gamma} - \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma})} \right\} \right] / \partial(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}) \Big|_{\boldsymbol{\gamma}=\boldsymbol{\gamma}^*} \right. \\ & \quad \times M\boldsymbol{\beta}_0^\top \mathbf{X}_i(\xi_1) - \sum_{i=1}^n \partial \left([g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}) | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}\}] \right. \\ & \quad \left. \times [\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}\}] \right) / \partial(\boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\gamma}) \Big|_{\boldsymbol{\gamma}=\boldsymbol{\gamma}^*} M\boldsymbol{\beta}_0^\top \mathbf{X}_i(\xi_1) \left. \right), \end{aligned}$$

with $E\{C_{9i}(t)\} \neq 0$, $E\{C_{9i}(t)\} < \infty$, and $\|C_{9i}(\cdot)\|_2 < \infty$. By Lemma 3, we have $\|\mathbf{T}_2\|_\infty = O_p\{h_b(h^2 + n^{-1/2}h^{-1/2})a_n\}$. Combining the orders of \mathbf{T}_0 , \mathbf{T}_1 and \mathbf{T}_2 , we see that \mathbf{T}_0 clearly dominates \mathbf{T}_1 , \mathbf{T}_2 . So we can write $\mathbf{T} = \mathbf{T}_0 + o_p(\mathbf{T}_0)$.

We further analyze \mathbf{T}_0 . Note that

$$\mathbf{T}_0 = \mathbf{T}_{00} + \mathbf{T}_{01} + \mathbf{T}_{02},$$

where

$$\begin{aligned} \mathbf{T}_{00} &= \left(n^{-1} \sum_{i=1}^n \frac{\partial [g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]}{\partial \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)} \boldsymbol{\Theta}_\gamma \right. \\ &\quad \times \left. [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]^\top \boldsymbol{\beta}_0 \boldsymbol{\beta}_0^\top [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \boldsymbol{\Theta}_\gamma^\top \right) \\ &= \left(n^{-1} \sum_{i=1}^n \boldsymbol{\Theta}_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]^\top \boldsymbol{\beta}_0 \right. \\ &\quad \times \left. \frac{\partial [g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]}{\partial \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)} \boldsymbol{\beta}_0^\top \right. \\ &\quad \left. [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \boldsymbol{\Theta}_\gamma^\top \right), \\ \mathbf{T}_{01} &= \left\{ n^{-1} \sum_{i=1}^n \partial \left([g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right. \right. \\ &\quad \left. \left. / \partial \{\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \boldsymbol{\Theta}_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]^\top \boldsymbol{\beta}_0 \right) \boldsymbol{\beta}_0^\top \right. \\ &\quad \left. \times [E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \boldsymbol{\Theta}_\gamma^\top \right\}, \end{aligned}$$

and

$$\begin{aligned} \mathbf{T}_{02} &= \left\{ n^{-1} \sum_{i=1}^n [g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right. \\ &\quad \left. \times \partial \left(\boldsymbol{\Theta}_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]^\top \boldsymbol{\beta}_0 \right) / \partial \{\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \boldsymbol{\beta}_0^\top \mathbf{Z}_i \boldsymbol{\Theta}_\gamma^\top \right\}. \end{aligned}$$

Now

$$\|\mathbf{T}_{00}\|_\infty = \max_{k=1, \dots, d_\gamma} \left| n^{-1} \sum_{i=1}^n \int_0^1 a_n C_{10i}(t) \{B_{rk}(t)\} dt \right|,$$

where

$$C_{10i}(t) = a_n^{-1} [\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]$$

$$\begin{aligned} & \times \frac{\partial [g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]}{\partial \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)} M \\ & \times \boldsymbol{\beta}_0^\top [\mathbf{X}_i(\xi_1) - E\{\mathbf{X}_i(\xi_1) | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]. \end{aligned}$$

Now $E\{C_{10i}(t)\} \neq 0$, $E\{C_{10i}(t)\} < \infty$ and $\|C_{10i}(\cdot)\|_2 < \infty$. By Lemma 3, we have $\|\mathbf{T}_{00}\|_\infty = O_p(h_b a_n)$. Similarly

$$\|\mathbf{T}_{01} + \mathbf{T}_{02}\|_\infty = \max_{k=1, \dots, d_\gamma} |n^{-1} \sum_{i=1}^n \int_0^1 a_n C_{11i}(t) \{B_{rk}(t)\} dt|,$$

where

$$\begin{aligned} C_{11i}(t) &= a_n^{-1} \partial \left([g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right. \\ & \quad \left. / \partial \{\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \boldsymbol{\Theta}_\gamma [\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right) \\ & \quad \times M \boldsymbol{\beta}_0^\top [E\{\mathbf{X}_i(\xi_1) | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] + a_n^{-1} [g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) \\ & \quad - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)) | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \partial \left([\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 \right. \\ & \quad \left. - E\{\mathbf{X}_i(t)^\top \boldsymbol{\beta}_0 | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right) / \partial \{\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} M \boldsymbol{\beta}_0^\top \mathbf{X}_i(\xi_1). \end{aligned}$$

Now $E\{C_{11i}(t)\} = 0$ and $\|C_{11i}(\cdot)\|_2 < \infty$. By Lemma 3, we have

$$\|\mathbf{T}_{01} + \mathbf{T}_{02}\|_\infty = O_p\{\sqrt{h_b n^{-1} \log(n)} a_n\} = o_p(\mathbf{T}_{00}) \quad (\text{S23})$$

by Condition (A4). Combining the results that $\mathbf{T} = \mathbf{T}_0 + o_p(\mathbf{T}_0)$ and $\mathbf{T}_0 = \mathbf{T}_{00} + o_p(\mathbf{T}_{00})$, we have

$$\mathbf{T} = \mathbf{T}_{00} + o_p(\mathbf{T}_{00}). \quad (\text{S24})$$

The Asymptotic Property of $\widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)$ Combining the above results with (S5), (S21) and (S24), we obtain

$$\begin{aligned} & n^{1/2} \{\widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\} \\ &= -\mathbf{T}^{-1} \mathbf{R} \\ &= -\left\{ \mathbf{T}_{00} + o_p(\mathbf{T}_{00}) \right\}^{-1} \{\mathbf{R}_{00} + o_p(\mathbf{R}_{00})\} \end{aligned}$$

$$\begin{aligned}
&= -E \left(\Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}]^\top \beta_0 \right. \\
&\quad \times \frac{\partial [g^*(Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)) - E\{g^*(Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)) | \beta_0^\top \alpha_0(\mathbf{X}_i)\}]}{\partial \beta_0^\top \alpha_0(\mathbf{X}_i)} \\
&\quad \times \beta_0^\top [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma^\top \left. \right)^{-1} \{\mathbf{R}_{00} + o_p(\mathbf{R}_{00})\} \\
&\quad - \left\{ \mathbf{T}_{00} + o_p(\mathbf{T}_{00}) \right\}^{-1} \{\mathbf{R}_{00} + o_p(\mathbf{R}_{00})\} \\
&\quad + E \left(\Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}]^\top \beta_0 \right. \\
&\quad \times \frac{\partial [g^*(Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)) - E\{g^*(Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)) | \beta_0^\top \alpha_0(\mathbf{X}_i)\}]}{\partial \beta_0^\top \alpha_0(\mathbf{X}_i)} \\
&\quad \times \beta_0^\top [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma^\top \left. \right)^{-1} \{\mathbf{R}_{00} + o_p(\mathbf{R}_{00})\} \\
&= -\{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^\top\}^{-1} n^{-1/2} \sum_{i=1}^n [g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} \\
&\quad - E\{g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma \\
&\quad \times \{\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}\}^\top \beta_0 + o_p(\mathbf{R}_{00}) \\
&\quad - [\Theta_\gamma \widehat{\mathbf{C}}_Q(\beta_0) \Theta_\gamma^\top + o_p\{\Theta_\gamma \widehat{\mathbf{C}}_Q(\beta_0) \Theta_\gamma^\top\}]^{-1} \left(n^{-1/2} \sum_{i=1}^n [g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} \right. \\
&\quad - E\{g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma \{\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}\}^\top \beta_0 \\
&\quad \left. + o_p(\mathbf{R}_{00}) \right) + \{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^\top\}^{-1} \left(n^{-1/2} \sum_{i=1}^n [g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} \right. \\
&\quad - E\{g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \\
&\quad \times \Theta_\gamma \{\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}\}^\top \beta_0 + o_p(\mathbf{R}_{00}) \left. \right) \\
&= - \left(\{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^\top\}^{-1} + o_p[\{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^\top\}^{-1}] \right) \\
&\quad \times \left(n^{-1/2} \sum_{i=1}^n [g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \right. \\
&\quad \left. \Theta_\gamma \{\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}\}^\top \beta_0 + o_p(\mathbf{R}_{00}) \right), \tag{S25}
\end{aligned}$$

where $\widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0)$, $\mathbf{C}_{\mathbf{Q}}(\boldsymbol{\beta}_0)$ are defined in Corollary 1 for $\mathbf{v} = \boldsymbol{\beta}_0$ and the corresponding

$$\begin{aligned} & \mathbf{Q}_i(t) \\ \equiv & \left(\frac{\partial [g^*(Y_i, \boldsymbol{\beta}_0^{\mathbf{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)) - E\{g^*(Y_i, \boldsymbol{\beta}_0^{\mathbf{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)) | \boldsymbol{\beta}_0^{\mathbf{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]}{\partial \boldsymbol{\beta}_0^{\mathbf{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)} \right)^{1/2} \\ & \times [\mathbf{X}_i(t) - E\{\mathbf{X}_i(t) | \boldsymbol{\beta}_0^{\mathbf{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]. \end{aligned}$$

The last equality holds because for arbitrary $d_{\gamma-1}$ -dimensional unit vector $\mathbf{u} \equiv (u_1, \dots, u_{\gamma-1})^{\mathbf{T}}$, we have $\mathbf{u}^{\mathbf{T}} \boldsymbol{\Theta}_{\gamma} = \{-\sum_{k=1}^{\gamma-1} u_k B_{rk+1}(0)/B_{r1}(0), u_1, \dots, u_{\gamma-1}\}^{\mathbf{T}}$. Now since $B_{rk+1}(0)$ is positive for at most r k 's, $\sum_{k=1}^{\gamma-1} u_k B_{rk+1}(0)/B_{r1}(0)$ is finite, which implies $\|\boldsymbol{\Theta}_{\gamma}^{\mathbf{T}} \mathbf{u}\|_2^2 = 1 - u_1^2 + \{\sum_{k=1}^{\gamma-1} u_k B_{rk+1}(0)/B_{r1}(0)\}^2$ and $\|\boldsymbol{\Theta}_{\gamma}\|_2 = O_p(1)$. Therefore,

$$D_7 \|\boldsymbol{\Theta}_{\gamma}^{\mathbf{T}} \mathbf{u}\|_2 h_b \leq \mathbf{u}^{\mathbf{T}} \boldsymbol{\Theta}_{\gamma} \widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}^{\mathbf{T}} \mathbf{u} \leq D_8 \|\boldsymbol{\Theta}_{\gamma}^{\mathbf{T}} \mathbf{u}\|_2 h_b \quad (\text{S26})$$

for bounded positive constants D_7, D_8 by Corollary 1, which implies the maximum and minimum eigenvalue of $\boldsymbol{\Theta}_{\gamma} \widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}$ is bounded between $D_7 \|\boldsymbol{\Theta}_{\gamma}^{\mathbf{T}} \mathbf{u}\|_2 h_b$ and $D_8 \|\boldsymbol{\Theta}_{\gamma}^{\mathbf{T}} \mathbf{u}\|_2 h_b$. Since $\boldsymbol{\Theta}_{\gamma} \widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}$ is a symmetric matrix, $\|\boldsymbol{\Theta}_{\gamma} \widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}\|_2$ is its maximum eigenvalue, which is of order $O_p(h_b)$. Now note that $\|\{\boldsymbol{\Theta}_{\gamma} \widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}\}^{-1}\|_2$ is the inverse of the minimum eigenvalue of $\boldsymbol{\Theta}_{\gamma} \widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}$. Therefore, $\|\{\boldsymbol{\Theta}_{\gamma} \widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}\}^{-1}\|_2 = O_p(h_b^{-1})$. In summary,

$$\begin{aligned} \|\boldsymbol{\Theta}_{\gamma} \widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}\|_2 &= O_p(h_b), \\ \|\{\boldsymbol{\Theta}_{\gamma} \widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}\}^{-1}\|_2 &= O_p(h_b^{-1}) \end{aligned} \quad (\text{S27})$$

Similar to those arguments that led to (S27), we have

$$\begin{aligned} \|\boldsymbol{\Theta}_{\gamma} \mathbf{C}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}\|_2 &= O_p(h_b), \\ \|\{\boldsymbol{\Theta}_{\gamma} \mathbf{C}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}\}^{-1}\|_2 &= O_p(h_b^{-1}). \end{aligned} \quad (\text{S28})$$

Now because as shown in Corollary 1, $\|\widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0) - \mathbf{C}_{\mathbf{Q}}(\boldsymbol{\beta}_0)\|_2 \leq o_p\{h_b n^{(h_b-1)/2}\}$ and $\|\boldsymbol{\Theta}_{\gamma}\|_2 = O_p(1)$, we have

$$\|\boldsymbol{\Theta}_{\gamma} \widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}^{\mathbf{T}} + o_p\{\boldsymbol{\Theta}_{\gamma} \widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}^{\mathbf{T}}\} - \boldsymbol{\Theta}_{\gamma} \mathbf{C}_{\mathbf{Q}}(\boldsymbol{\beta}_0) \boldsymbol{\Theta}_{\gamma}^{\mathbf{T}}\|_2$$

$$\begin{aligned}
&\leq \|\Theta_\gamma \widehat{\mathbf{C}}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T - \Theta_\gamma \mathbf{C}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T\|_2 + o_p\{\|\Theta_\gamma \widehat{\mathbf{C}}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T\|_2\} \\
&\leq o_p\{h_b n^{(h_b-1)/2}\} + o_p(h_b).
\end{aligned}$$

Therefore,

$$\begin{aligned}
&\|[\Theta_\gamma \widehat{\mathbf{C}}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T + o_p\{\Theta_\gamma \widehat{\mathbf{C}}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T\}]^{-1} - \{\Theta_\gamma \mathbf{C}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T\}^{-1}\|_2 \\
&= \|\{\Theta_\gamma \mathbf{C}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T\}^{-2} [\Theta_\gamma \widehat{\mathbf{C}}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T + o_p\{\Theta_\gamma \widehat{\mathbf{C}}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T\} \\
&\quad - \Theta_\gamma \mathbf{C}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T] \{1 + o_p(1)\}\|_2 \\
&\leq o_p\{h_b^{-2} h_b n^{(h_b-1)/2}\} + o_p(h_b^{-2} h_b) \\
&= o_p\{h_b^{-1} n^{(h_b-1)/2}\} + o_p(h_b^{-1}) \\
&= o_p[\{\Theta_\gamma \mathbf{C}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T\}^{-1}]. \tag{S29}
\end{aligned}$$

As a result, (S25) holds and we can write

$$\begin{aligned}
&n^{1/2}\{\widehat{\gamma}^-(\beta_0) - \gamma_0^-\} \\
&= -(\{\Theta_\gamma \mathbf{C}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T\}^{-1} + o_p[\{\Theta_\gamma \mathbf{C}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T\}^{-1}]) \left(n^{-1/2} \sum_{i=1}^n [g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} \right. \\
&\quad \left. E\{g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)\} \Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}]^T \beta_0 + o_p(\mathbf{R}_{00}) \right) \\
&= -\left(\left\{ E \left(\Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}]^T \beta_0 \right. \right. \right. \\
&\quad \times \frac{\partial (g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} - E[g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)])}{\partial \beta_0^T \alpha_0(\mathbf{X}_i)} \\
&\quad \left. \left. \times \beta_0^T [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma^T \right\}^{-1} + o_p[\{\Theta_\gamma \mathbf{C}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T\}^{-1}] \right) \\
&\quad \times \left(n^{-1/2} \sum_{i=1}^n [g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma \right. \\
&\quad \left. \times [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}]^T \beta_0 + o_p(\mathbf{R}_{00}) \right) \\
&= \mathbf{L} + o_p(\mathbf{L}),
\end{aligned}$$

where recall that we have defined in the statement that

$$\mathbf{L} = -\{\Theta_\gamma \mathbf{C}_{\mathbf{Q}}(\beta_0) \Theta_\gamma^T\}^{-1} \left(n^{-1/2} \sum_{i=1}^n [g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} \right.$$

$$\begin{aligned}
& -E\{g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)\} \Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}]^T \beta_0) \\
= & -\left(\left\{ E\left(\Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}]^T \beta_0 \right. \right. \right. \quad (\text{S30}) \\
& \times \frac{\partial (g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} - E[g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)])}{\partial \beta_0^T \alpha_0(\mathbf{X}_i)} \\
& \times \beta_0^T [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma^T \left. \right\}^{-1} \left(n^{-1/2} \sum_{i=1}^n [g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} \right. \\
& \left. - E\{g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}]^T \beta_0 \right).
\end{aligned}$$

Now for arbitrary $d_{\gamma-1}$ -dimensional vector \mathbf{a} with $\|\mathbf{a}\|_2 < \infty$ by using the same argument as those lead to (S23), we have

$$\begin{aligned}
[\mathbf{a}^T n^{1/2} \{\widehat{\gamma}^-(\beta_0) - \gamma_0^-\}]^2 &= \mathbf{a}^T \mathbf{L} \mathbf{L}^T \mathbf{a} + o_p(\mathbf{a}^T \mathbf{L} \mathbf{L}^T \mathbf{a}) \\
&= \mathbf{L}_1 + o_p(\mathbf{L}_1),
\end{aligned}$$

where

$$\begin{aligned}
\mathbf{L}_1 &= -\|\mathbf{a}^T \{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^T\}^{-1}\|_2^2 \frac{\mathbf{a}^T \{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^T\}^{-1}}{\|\mathbf{a}^T \{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^T\}^{-1}\|_2} \\
&\quad \times n^{-1} \sum_{i=1}^n \left([g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma [\mathbf{Z}_i \right. \\
&\quad \left. - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}]^T \beta_0 \right)^{\otimes 2} \frac{\{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^T\}^{-1} \mathbf{a}}{\|\mathbf{a}^T \{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^T\}^{-1}\|_2} \\
&= -\|\mathbf{a}^T \{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^T\}^{-1}\|_2^2 \frac{\mathbf{a}^T \{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^T\}^{-1}}{\|\mathbf{a}^T \{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^T\}^{-1}\|_2} \\
&\quad n^{-1} \sum_{i=1}^n \left([g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma [\mathbf{Z}_i \right. \\
&\quad \left. - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}]^T \beta_0 \right)^{\otimes 2} \frac{\{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^T\}^{-1} \mathbf{a}}{\|\mathbf{a}^T \{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^T\}^{-1}\|_2} \\
&\leq O_p(h_b^{-2} h_b) \\
&= O_p(h_b^{-1}).
\end{aligned}$$

The third line holds by noting that $\|\{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^\top\}^{-1}\| = O_p(h_b^{-1})$ by (S28) and

$$n^{-1} \sum_{i=1}^n \left([g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma \right. \\ \left. \times \{\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}\}^\top \beta_0 \right)^{\otimes 2}$$

is in the form of $\Theta_\gamma \widehat{\mathbf{C}}_Q(\beta_0) \Theta_\gamma^\top$, where $\widehat{\mathbf{C}}_Q(\beta_0)$ is defined in Corollary 1 with $\mathbf{v} = \beta_0$ and

$$\begin{aligned} & \mathbf{Q}_i(t) \\ & \equiv [g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \\ & \quad \times [\mathbf{X}_i(t) - E\{\mathbf{X}_i(t) | \beta_0^\top \alpha_0(\mathbf{X}_i)\}]. \end{aligned}$$

Using the arguments as those led to (S26), we have

$$\begin{aligned} D_{10} h_b & \leq \frac{\mathbf{a}^\top \{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^\top\}^{-1}}{\|\mathbf{a}^\top \{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^\top\}^{-1}\|_2} n^{-1} \sum_{i=1}^n \left([g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} \right. \\ & \quad \left. - E\{g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma \{\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}\}^\top \beta_0 \right)^{\otimes 2} \\ & \quad \times \frac{\{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^\top\}^{-1} \mathbf{a}}{\|\mathbf{a}^\top \{\Theta_\gamma \mathbf{C}_Q(\beta_0) \Theta_\gamma^\top\}^{-1}\|_2} \leq D_{11} h_b, \end{aligned} \tag{S31}$$

where D_{10} and D_{11} are positive constants. Therefore $\mathbf{a}^\top \{\widehat{\gamma}^-(\beta_0) - \gamma_0^-\} = O_p(n^{-1/2} h_b^{-1/2})$. This proves the result. \square

S3.2 Proof of Theorem 2

The proof of Theorem 2 is divided into two parts. In Part I, we show that $\sqrt{n}(\widehat{\beta} - \beta)$ converges to a random quantity which exists under the approximated model. In Part II, we show that this quantity converges to a Gaussian vector defined on the measurable space under the true model.

Part I

By the consistency shown in Proposition 2, we expand the score function as

$$\mathbf{0} = n^{-1/2} \sum_{i=1}^n \left[g^*\{Y_i, \widehat{\beta}^\top \mathbf{Z}_i \widehat{\gamma}(\widehat{\beta})\} \right]$$

$$\begin{aligned}
& - \frac{\sum_{j=1}^J K_h \{ \hat{\boldsymbol{\beta}}^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\hat{\boldsymbol{\beta}}) - \hat{\boldsymbol{\beta}}^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\hat{\boldsymbol{\beta}}) \} g^* \{ Y_j, \hat{\boldsymbol{\beta}}^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\hat{\boldsymbol{\beta}}) \}}{\sum_{j=1}^J K_h \{ \hat{\boldsymbol{\beta}}^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\hat{\boldsymbol{\beta}}) - \hat{\boldsymbol{\beta}}^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\hat{\boldsymbol{\beta}}) \}} \Big] \boldsymbol{\Theta}_\beta \\
& \times \left[\mathbf{Z}_i - \frac{\sum_{j=1}^J K_h \{ \hat{\boldsymbol{\beta}}^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\hat{\boldsymbol{\beta}}) - \hat{\boldsymbol{\beta}}^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\hat{\boldsymbol{\beta}}) \} \mathbf{Z}_j}{\sum_{j=1}^J K_h \{ \hat{\boldsymbol{\beta}}^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\hat{\boldsymbol{\beta}}) - \hat{\boldsymbol{\beta}}^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\hat{\boldsymbol{\beta}}) \}} \right] \hat{\boldsymbol{\gamma}}(\hat{\boldsymbol{\beta}}) \\
& = \mathbf{G} + \mathbf{H} n^{1/2} (\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0), \tag{S32}
\end{aligned}$$

where

$$\begin{aligned}
\mathbf{G} & = n^{-1/2} \sum_{i=1}^n \left[g^* \{ Y_i, \boldsymbol{\beta}_0^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) \} \right. \\
& \quad \left. - \frac{\sum_{j=1}^J K_h \{ \boldsymbol{\beta}_0^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \boldsymbol{\beta}_0^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) \} g^* \{ Y_j, \boldsymbol{\beta}_0^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) \}}{\sum_{j=1}^J K_h \{ \boldsymbol{\beta}_0^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \boldsymbol{\beta}_0^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) \}} \right] \boldsymbol{\Theta}_\beta \\
& \quad \times \left[\mathbf{Z}_i - \frac{\sum_{j=1}^J K_h \{ \boldsymbol{\beta}_0^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \boldsymbol{\beta}_0^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) \} \mathbf{Z}_j}{\sum_{j=1}^J K_h \{ \boldsymbol{\beta}_0^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \boldsymbol{\beta}_0^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) \}} \right] \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)
\end{aligned}$$

and

$$\begin{aligned}
\mathbf{H} & = n^{-1} \sum_{i=1}^n \partial \left[g^* \{ Y_i, \boldsymbol{\beta}^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) \} \right. \\
& \quad \left. - \frac{\sum_{j=1}^J K_h \{ \boldsymbol{\beta}^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) - \boldsymbol{\beta}^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) \} g^* \{ Y_j, \boldsymbol{\beta}^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) \}}{\sum_{j=1}^J K_h \{ \boldsymbol{\beta}^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) - \boldsymbol{\beta}^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) \}} \right] \boldsymbol{\Theta}_\beta \\
& \quad \times \left[\mathbf{Z}_i - \frac{\sum_{j=1}^J K_h \{ \boldsymbol{\beta}^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) - \boldsymbol{\beta}^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) \} \mathbf{Z}_j}{\sum_{j=1}^J K_h \{ \boldsymbol{\beta}^T \mathbf{Z}_j \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) - \boldsymbol{\beta}^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) \}} \right] \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) / \partial \boldsymbol{\beta}^T |_{\boldsymbol{\beta}=\boldsymbol{\beta}^*},
\end{aligned}$$

where $\boldsymbol{\beta}^*$ is the point on the line connecting $\hat{\boldsymbol{\beta}}$ and $\boldsymbol{\beta}_0$. In the following, we study the asymptotic properties for \mathbf{G} and \mathbf{H} separately.

The Asymptotic Property for \mathbf{G} Now we can decompose \mathbf{G} as

$$\mathbf{G} = \mathbf{G}_0 + \mathbf{G}_1 + \mathbf{G}_2 + \mathbf{G}_3,$$

where

$$\begin{aligned}
\mathbf{G}_0 & = n^{-1/2} \sum_{i=1}^n \left(g^* \{ Y_i, \boldsymbol{\beta}_0^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) \} - E \left[g^* \{ Y_i, \boldsymbol{\beta}_0^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) \} | \boldsymbol{\beta}_0^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) \right] \right) \boldsymbol{\Theta}_\beta \\
& \quad \times \left[\mathbf{Z}_i - E \{ \mathbf{Z}_i | \boldsymbol{\beta}_0^T \mathbf{Z}_i \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) \} \right] \hat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0),
\end{aligned}$$

Note that $\mathbf{G}_{11}, \mathbf{G}_{12}$ are of finite dimension, so the sup norm and the L_2 norm are equivalent. Using the U-statistics techniques similar to those led to (S11) and (S13), we get

$$\begin{aligned}
\mathbf{G}_{11} &= n^{-3/2} \sum_{i=1}^n \sum_{j=1}^J (g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} - E[g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)]) \Theta_\beta \\
&\quad \times \left\{ \frac{E\{\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} K_h\{\beta_0^\top \mathbf{Z}_j \hat{\gamma}(\beta_0) - \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}} \right. \\
&\quad \left. - \frac{K_h\{\beta_0^\top \mathbf{Z}_j \hat{\gamma}(\beta_0) - \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} \mathbf{Z}_j}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}} \right\} \hat{\gamma}(\beta_0) \\
&= \mathbf{G}_{111} + \mathbf{G}_{112} - \mathbf{G}_{113} + o_p(\mathbf{G}_{111} + \mathbf{G}_{112} - \mathbf{G}_{113}),
\end{aligned}$$

where

$$\begin{aligned}
\mathbf{G}_{111} &= n^{-1/2} \sum_{i=1}^n E \left[(g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} - E[g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)]) \Theta_\beta \right. \\
&\quad \times \left\{ \frac{E\{\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} K_h\{\beta_0^\top \mathbf{Z}_j \hat{\gamma}(\beta_0) - \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}} \right. \\
&\quad \left. \left. - \frac{K_h\{\beta_0^\top \mathbf{Z}_j \hat{\gamma}(\beta_0) - \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} \mathbf{Z}_j}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}} \right\} \hat{\gamma}(\beta_0) | \mathbf{O}_i \right], \\
\mathbf{G}_{112} &= n^{-1/2} \sum_{j=1}^J E \left[(g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} - E[g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)]) \Theta_\beta \right. \\
&\quad \times \left\{ \frac{E\{\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} K_h\{\beta_0^\top \mathbf{Z}_j \hat{\gamma}(\beta_0) - \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}} \right. \\
&\quad \left. \left. - \frac{K_h\{\beta_0^\top \mathbf{Z}_j \hat{\gamma}(\beta_0) - \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} \mathbf{Z}_j}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}} \right\} \hat{\gamma}(\beta_0) | \mathbf{O}_j \right], \\
\mathbf{G}_{113} &= n^{1/2} E \left[(g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} - E[g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)]) \Theta_\beta \right. \\
&\quad \times \left\{ \frac{E\{\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} K_h\{\beta_0^\top \mathbf{Z}_j \hat{\gamma}(\beta_0) - \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}} \right. \\
&\quad \left. \left. - \frac{K_h\{\beta_0^\top \mathbf{Z}_j \hat{\gamma}(\beta_0) - \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} \mathbf{Z}_j}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}} \right\} \hat{\gamma}(\beta_0) \right].
\end{aligned}$$

Similar to \mathbf{R}_{111} , using the same derivation in (S7), we can write the summand of \mathbf{G}_{111} as

$$E \left[(g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} - E[g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)]) \Theta_\beta \right.$$

$$\begin{aligned}
& \times \left\{ \frac{E\{\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} K_h\{\beta_0^\top \mathbf{Z}_j \hat{\gamma}(\beta_0) - \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}} \right. \\
& \left. - \frac{K_h\{\beta_0^\top \mathbf{Z}_j \hat{\gamma}(\beta_0) - \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} \mathbf{Z}_j}{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}} \right\} \hat{\gamma}(\beta_0) | \mathbf{O}_i \Big] \\
= & (g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} - E[g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)]) \Theta_\beta \\
& \times \left(E\{\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} \hat{\gamma}(\beta_0) \int \frac{\partial^2 f_{\mathbf{Z}}[c\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0), sh\}]}{\partial c\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0), sh\}^2} \frac{s^2 K(s)}{2f_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}} ds \right. \\
& \left. - \int \frac{\partial^2 [E\{\mathbf{Z}_i | d\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0), sh\}\} \hat{\gamma}(\beta_0) f_{\mathbf{Z}}\{d\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0), sh\}\}]}{\partial d\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0), sh\}^2} \right. \\
& \left. \times \frac{s^2 K(s)}{2f_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}} ds \right) h^2,
\end{aligned}$$

which is a mean $\mathbf{0}$ finite dimensional vector. Here $c\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0), sh\}$ and $d\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0), sh\}$ are points on the line connecting $\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)$ and $\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0) + sh$. Therefore, we have $\|h^{-2} \mathbf{G}_{111}\| = O_p(1)$, and in turn \mathbf{G}_{111} and \mathbf{G}_{113} have the order of $O_p(h^2)$. Further, similar to \mathbf{R}_{112} , we have $\mathbf{G}_{112} = \mathbf{0}$. As a result, $\mathbf{G}_{11} = \mathbf{G}_{111} + \mathbf{G}_{112} - \mathbf{G}_{113} + o_p(\mathbf{G}_{111} + \mathbf{G}_{112} - \mathbf{G}_{113}) = O_p(h^2)$. Now similar to (S12), since

$$\left\{ \frac{nf_{\mathbf{Z}}\{\beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}}{\sum_{j=1}^J K_h\{\beta_0^\top \mathbf{Z}_j \hat{\gamma}(\beta_0) - \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}} - 1 \right\} = O_p\{h^2 + (nh)^{-1/2}\},$$

we obtain $\mathbf{G}_{12} = o_p(\mathbf{G}_{11})$. Thus, we have

$$\|\mathbf{G}_1\|_2 = \|\mathbf{G}_{11} + \mathbf{G}_{12}\|_2 = O_p(h^2). \tag{S33}$$

Using similar derivation as those led to (S33) while exchanging the roles of \mathbf{Z} and g^* , we obtain $\|\mathbf{G}_2\|_2 = O_p(h^2)$. Using the same reasoning as those led to (S16), and noting that \mathbf{G}_3 is a finite dimensional vector, we have that the order of \mathbf{G}_3 is the same as $n^{1/2}$ times the square of the order for kernel estimation errors, i.e., $\|\mathbf{G}_3\|_2 = O_p(n^{1/2}h^4 + n^{-1/2}h^{-1}) = o_p(1)$ under Condition (A2).

Now we can further write $\mathbf{G}_0 = \mathbf{G}_{00} + \mathbf{G}_{01} + \mathbf{G}_{02}$, where

$$\begin{aligned}
\mathbf{G}_{00} &= n^{-1/2} \sum_{i=1}^n (g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} - E[g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)]) \Theta_\beta \\
&\quad \times [\alpha_0(\mathbf{X}_i) - E\{\alpha_0(\mathbf{X}_i) | \beta_0^\top \alpha_0(\mathbf{X}_i)\}],
\end{aligned}$$

$$\begin{aligned}
\mathbf{G}_{01} &= n^{-1/2} \sum_{i=1}^n (g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} - E[g^*\{Y_i, \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\} | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)]) \Theta_\beta \\
&\quad \times [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \hat{\gamma}(\beta_0)\}] \hat{\gamma}(\beta_0) - n^{-1/2} \sum_{i=1}^n [g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) \\
&\quad - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\beta \{\mathbf{Z}_i - E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0)\} \gamma_0, \\
\mathbf{G}_{02} &= n^{-1/2} \sum_{i=1}^n [g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\beta \{\mathbf{Z}_i \\
&\quad - E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0)\} \gamma_0 - n^{-1/2} \sum_{i=1}^n (g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} \\
&\quad - E[g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)]) \Theta_\beta [\alpha_0(\mathbf{X}_i) - E\{\alpha_0(\mathbf{X}_i) | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \\
&= n^{-1/2} \sum_{i=1}^n (g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} - E[g^*\{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)]) \Theta_\beta \\
&\quad \times \frac{\partial [\alpha_0(\mathbf{X}_i) - E\{\alpha_0(\mathbf{X}_i) | \beta_0^\top \alpha_0(\mathbf{X}_i)\}]}{\partial \alpha_0(\mathbf{X}_i)} \Big|_{\alpha_0 = \alpha_0^*(\mathbf{X}_i, \mathbf{Z}_i)} \{\mathbf{Z}_i \gamma_0 - \alpha_0(\mathbf{X}_i)\},
\end{aligned}$$

where $\alpha_0^*(\mathbf{X}_i, \mathbf{Z}_i)$ is the point on the line connecting $\alpha_0(\mathbf{X}_i)$ and $\mathbf{Z}_i \gamma_0$. Clearly we have $E(\mathbf{G}_{02}) = 0$. Further from $\|\mathbf{B}_r(\cdot)^\top \gamma_0 - \alpha_0(\cdot)\|_\infty = O_p(h_b^q)$, we have

$$\begin{aligned}
&\|\mathbf{Z}_i \gamma_0 - \alpha_0(\mathbf{X}_i)\|_2 \\
&= \left\| \int_0^1 \mathbf{B}_r(t)^\top \gamma_0 \mathbf{X}_i(t) dt - \int_0^1 \alpha_0(t) \mathbf{X}_i(t) dt \right\|_2 \\
&\leq \left\{ \int_0^1 |\mathbf{B}_r(t)^\top \gamma_0 - \alpha_0(t)|^2 dt \right\}^{1/2} \|\mathbf{X}_i(\cdot)\|_2 \\
&= O_p(h_b^q),
\end{aligned}$$

so $\|h_b^{-q} \mathbf{G}_{02}\|_2 = O_p(1)$. Therefore, $\|\mathbf{G}_{02}\|_2 = O_p(h_b^q)$.

Next

$$\begin{aligned}
&\mathbf{G}_{01} \\
&= \left(n^{-1} \sum_{i=1}^n \frac{\partial [g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \beta_0^\top \mathbf{Z}_i \gamma_0) | \beta_0^\top \mathbf{Z}_i \gamma_0\}] \Theta_\beta \{\mathbf{Z}_i - E(\mathbf{Z}_i | \beta_0^\top \mathbf{Z}_i \gamma_0)\} \gamma_0}{\partial \gamma_0^{-\top}} \right. \\
&\quad \left. n^{1/2} \{\hat{\gamma}^-(\beta_0) - \gamma_0^-\} \right) \{1 + o_p(1)\} \\
&= \mathbf{G}_{011}^\top n^{1/2} \{\hat{\gamma}^-(\beta_0) - \gamma_0^-\} \{1 + o_p(1)\},
\end{aligned}$$

where

$$\begin{aligned} & \mathbf{G}_{011}^T \\ = & n^{-1} \sum_{i=1}^n \frac{\partial [g^*(Y_i, \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0) | \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0\}]}{\partial \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0} \boldsymbol{\Theta}_\beta \{\mathbf{Z}_i - E(\mathbf{Z}_i | \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0)\} \gamma_0 \\ & \times \boldsymbol{\beta}_0^T \{\mathbf{Z}_i - E(\mathbf{Z}_i | \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0)\} \boldsymbol{\Theta}_\gamma^T. \end{aligned}$$

The last equality holds by using the same arguments as those lead to (S23)

Now

$$\mathbf{G}_{011}^T = n^{-1} \sum_{i=1}^n \int_0^1 \mathbf{C}_{12i}(t) \mathbf{B}_r^T(t) \boldsymbol{\Theta}_\gamma^T dt$$

is a $(J-1) \times (d_\gamma - 1)$ matrix where

$$\begin{aligned} \mathbf{C}_{12i}(t) = & \frac{\partial [g^*(Y_i, \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0) | \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0\}]}{\partial \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0} \boldsymbol{\Theta}_\beta \{\mathbf{Z}_i - E(\mathbf{Z}_i | \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0)\} \gamma_0 \\ & \times [\boldsymbol{\beta}_0^T \mathbf{X}_i(t) - E\{\boldsymbol{\beta}_0^T \mathbf{X}_i(t) | \boldsymbol{\beta}_0^T \mathbf{Z}_i \gamma_0\}]. \end{aligned}$$

Because J is finite, $\|\mathbf{G}_{011}\|_\infty$ and $\|\mathbf{G}_{011l}\|_\infty$ have the same order as their elements did, where \mathbf{G}_{011l} is the l th column of \mathbf{G}_{011} . The (k, l) element of \mathbf{G}_{011} is

$$G_{011kl} = n^{-1} \sum_{i=1}^n \int_0^1 \{B_{rk}(t)\} C_{12li} dt,$$

where C_{12li} is the l th element of \mathbf{C}_{12i} . Now $E\{C_{12li}(t)\} \neq 0$, $|E\{C_{12li}(t)\}| < \infty$, $\|C_{12li}(\cdot)\|_2 < \infty$, *a.s.* by Condition (A6). Therefore, by Lemma 3 we have $|G_{011kl}| = O_p(h_b)$, and thus \mathbf{G}_{011l} and \mathbf{G}_{011} satisfy

$$\|\mathbf{G}_{011l}\|_\infty = O_p(h_b), \quad \|\mathbf{G}_{011}\|_\infty = O_p(h_b). \quad (\text{S34})$$

Since $\|\mathbf{a}\|_2 \leq N^{1/2} \|\mathbf{a}\|_\infty$ for arbitrary vector \mathbf{a} with length N , and $\|\mathbf{b}\|_2 \leq N^{1/2} \|\mathbf{b}\|_\infty$ for arbitrary matrix \mathbf{b} with N rows, we obtain

$$\begin{aligned} \|\mathbf{G}_{011l}\|_2 & \leq N^{1/2} O_p(h_b) = O_p(h_b^{1/2}), \\ \|\mathbf{G}_{011}\|_2 & \leq N^{1/2} O_p(h_b) = O_p(h_b^{1/2}). \end{aligned}$$

Therefore,

$$\begin{aligned}
& \mathbf{G}_{011}^T n^{1/2} \{\hat{\gamma}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\} \\
&= O_p[\max_{1 \leq l \leq J} \mathbf{G}_{011l}^T n^{1/2} \{\hat{\gamma}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\}] \\
&= h_b^{1/2} O_p[\max_{1 \leq l \leq J} h_b^{-1/2} \mathbf{G}_{011l}^T n^{1/2} \{\hat{\gamma}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\}] \\
&= O_p(1)
\end{aligned}$$

by Theorem 1 that $\|\mathbf{a}^T \{\hat{\gamma}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\}\| = O_p(n^{-1/2} h_b^{-1/2})$ for arbitrary \mathbf{a} with $\|\mathbf{a}\|_2 < \infty$.

Further,

$$\begin{aligned}
\mathbf{G}_{011}^T n^{1/2} \{\hat{\gamma}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\} &= \mathbf{G}_{013}^T n^{1/2} \{\hat{\gamma}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\} + (\mathbf{G}_{011} - \mathbf{G}_{012})^T n^{1/2} \{\hat{\gamma}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\} \\
&\quad + (\mathbf{G}_{012} - \mathbf{G}_{013})^T n^{1/2} \{\hat{\gamma}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\}
\end{aligned}$$

where

$$\begin{aligned}
& \mathbf{G}_{012}^T \\
&= E \left(\frac{\partial [g^*(Y_i, \boldsymbol{\beta}_0^T \mathbf{Z}_i \boldsymbol{\gamma}_0) - E\{g^*(Y_i, \boldsymbol{\beta}_0^T \mathbf{Z}_i \boldsymbol{\gamma}_0) | \boldsymbol{\beta}_0^T \mathbf{Z}_i \boldsymbol{\gamma}_0\}]}{\partial \boldsymbol{\beta}_0^T \mathbf{Z}_i \boldsymbol{\gamma}_0} \boldsymbol{\Theta}_\beta \{\mathbf{Z}_i - E(\mathbf{Z}_i | \boldsymbol{\beta}_0^T \mathbf{Z}_i \boldsymbol{\gamma}_0)\} \boldsymbol{\gamma}_0 \right. \\
&\quad \left. \times \boldsymbol{\beta}_0^T \{\mathbf{Z}_i - E(\mathbf{Z}_i | \boldsymbol{\beta}_0^T \mathbf{Z}_i \boldsymbol{\gamma}_0)\} \boldsymbol{\Theta}_\gamma^T \right)
\end{aligned}$$

and

$$\begin{aligned}
\mathbf{G}_{013}^T &= E \left\{ \frac{\partial [g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E[g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)]]}{\partial \{\boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}} \boldsymbol{\Theta}_\beta \right. \\
&\quad \left. \times [\boldsymbol{\alpha}_0(\mathbf{X}_i) - E\{\boldsymbol{\alpha}_0(\mathbf{X}_i) | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \boldsymbol{\beta}_0^T [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \boldsymbol{\Theta}_\gamma^T \right\}.
\end{aligned}$$

Therefore,

$$\mathbf{G}_{011}^T - \mathbf{G}_{012}^T = n^{-1} \sum_{i=1}^n \int_0^1 \mathbf{C}_{13i}(t) \mathbf{B}_r^T(t) \boldsymbol{\Theta}_\gamma^T dt,$$

where

$$= \frac{\mathbf{C}_{13i}}{\partial \boldsymbol{\beta}_0^T \mathbf{Z}_i \boldsymbol{\gamma}_0} \partial [g^*(Y_i, \boldsymbol{\beta}_0^T \mathbf{Z}_i \boldsymbol{\gamma}_0) - E\{g^*(Y_i, \boldsymbol{\beta}_0^T \mathbf{Z}_i \boldsymbol{\gamma}_0) | \boldsymbol{\beta}_0^T \mathbf{Z}_i \boldsymbol{\gamma}_0\}] \boldsymbol{\Theta}_\beta$$

$$\begin{aligned}
& \times \left\{ \mathbf{Z}_i - E(\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) \right\} \gamma_0 [\boldsymbol{\beta}_0^\top \mathbf{X}_i(t) - E\{\boldsymbol{\beta}_0^\top \mathbf{X}_i(t) | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\}] \\
& - E \left(\frac{\partial [g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) - E\{g^*(Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\}]}{\partial \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0} \boldsymbol{\Theta}_\beta \right. \\
& \left. \times \left\{ \mathbf{Z}_i - E(\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0) \right\} \gamma_0 [\boldsymbol{\beta}_0^\top \mathbf{X}_i(t) - E\{\boldsymbol{\beta}_0^\top \mathbf{X}_i(t) | \boldsymbol{\beta}_0^\top \mathbf{Z}_i \gamma_0\}] \right),
\end{aligned}$$

with its l th element $C_{13li}(t)$ satisfies $E\{C_{13li}(t)\} = 0$, $|E\{C_{13li}(t)\}| < \infty$, $\|C_{13li}(\cdot)\|_2 < \infty$, *a.s.* by Condition (A6). Therefore, using the similar argument as those led to (S34) and Lemma 3 we have

$$\|\mathbf{G}_{011} - \mathbf{G}_{012}\|_\infty = O_p\{\sqrt{h_b n^{-1} \log(n)}\} = o_p(h_b).$$

Further, $\|\mathbf{G}_{012} - \mathbf{G}_{013}\|_\infty = O_p(h_b^q)$ by Condition (A5). As a result, we have

$$\|\mathbf{G}_{012} - \mathbf{G}_{013}\|_\infty = o_p(\|\mathbf{G}_{011}\|_\infty) = o_p(h_b) \quad (\text{S35})$$

and

$$\|\mathbf{G}_{013}\|_2 \leq \sqrt{N} \|\mathbf{G}_{013}\|_\infty = \sqrt{N} O_p(\|\mathbf{G}_{011}\|_\infty) = O_p(h_b^{1/2}) \quad (\text{S36})$$

by (S34) and we can write

$$\mathbf{G}_{01} = \mathbf{G}_{013}^\top n^{1/2} \{\widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\} + o_p(1).$$

Combining with the result that $\|\mathbf{G}_{02}\| = O_p(h_b^q)$ and the fact that $\mathbf{G}_0 = \mathbf{G}_{00} + \mathbf{G}_{01} + \mathbf{G}_{02}$, we have

$$\begin{aligned}
\mathbf{G}_0 &= \mathbf{G}_{00} + \mathbf{G}_{013}^\top n^{1/2} \{\widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\} + o_p(1) \\
&= O_p(1).
\end{aligned}$$

Further, $\mathbf{G}_1 = O_p(h^2)$, $\mathbf{G}_2 = O_p(h^2)$ and $\mathbf{G}_3 = o_p(1)$, $\mathbf{G} = \mathbf{G}_0 + \mathbf{G}_1 + \mathbf{G}_2 + \mathbf{G}_3$, so we have

$$\begin{aligned}
\mathbf{G} &= \mathbf{G}_{00} + \mathbf{G}_{013}^\top n^{1/2} \{\widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\} + o_p(1) \\
&= O_p(1).
\end{aligned} \quad (\text{S37})$$

The Asymptotic Property for \mathbf{H} Note that \mathbf{H} is a finite dimensional vector, and

$$\begin{aligned}
& \|\mathbf{B}_r(\cdot)\widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \boldsymbol{\alpha}_0(\cdot)\|_\infty \\
& \leq \|\mathbf{B}_r(\cdot)\widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \mathbf{B}_r(\cdot)\boldsymbol{\gamma}_0\|_\infty \\
& \quad + \|\mathbf{B}_r(\cdot)\boldsymbol{\gamma}_0 - \boldsymbol{\alpha}_0(\cdot)\|_\infty \\
& = O_p(n^{-1/2}h^{-1/2} + h_b^q) \\
& = o_p(1).
\end{aligned}$$

Now by the fact that the kernel estimators are uniformly consistent, we have

$$\mathbf{H} = \mathbf{H}_0 + \mathbf{H}_1 + o_p(1),$$

where

$$\begin{aligned}
\mathbf{H}_0 &= E\{\partial(g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}) - E[g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}|\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)]\} \boldsymbol{\Theta}_\beta \\
& \quad \times [\boldsymbol{\alpha}_0(\mathbf{X}_i) - E\{\boldsymbol{\alpha}_0(\mathbf{X}_i)|\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] / \partial \boldsymbol{\beta}_0^\top \boldsymbol{\Theta}_\beta^\top, \tag{S38}
\end{aligned}$$

$$\begin{aligned}
\mathbf{H}_1 &= n^{-1} \sum_{i=1}^n [\partial\{(g^*\{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)\}) - E[g^*\{Y_i, \boldsymbol{\beta}_0^\top \mathbf{Z}_i \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)\}|\boldsymbol{\beta}_0^\top \mathbf{Z}_i \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)]\} \boldsymbol{\Theta}_\beta \\
& \quad \times [\mathbf{Z}_i - E\{\mathbf{Z}_i|\boldsymbol{\beta}_0^\top \mathbf{Z}_i \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)\}] \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)\} / \partial \widehat{\boldsymbol{\gamma}}^\top(\boldsymbol{\beta}_0)] \partial \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) / \partial \boldsymbol{\beta}^\top |_{\boldsymbol{\beta}=\boldsymbol{\beta}^*} \\
& = \mathbf{G}_{011}^\top \partial \widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta}) / \partial \boldsymbol{\beta}^\top |_{\boldsymbol{\beta}=\boldsymbol{\beta}^*} \{1 + o_p(1)\} \\
& = \mathbf{G}_{013}^\top \partial \widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta}) / \partial \boldsymbol{\beta}^\top |_{\boldsymbol{\beta}=\boldsymbol{\beta}^*} \{1 + o_p(1)\} \\
& = \mathbf{G}_{013}^\top \mathbf{P} \{1 + o_p(1)\} \\
& = \mathbf{G}_{013}^\top \mathbf{P} + o_p(1), \tag{S39}
\end{aligned}$$

where \mathbf{P} is defined in (S53). The second equality holds because $\widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0)$ is consistent to $\boldsymbol{\gamma}_0$. The third equality holds by (S35). The fourth equality holds by (S52). The last equality holds because $\|\mathbf{G}_{013}\|_2 = O_p(h_b^{1/2})$ by (S36), and $\|\mathbf{P}\|_2 = O_p(h_b^{-1/2})$ by (S54). Combining (S37), (S38), (S39) and (S32), we have

$$\sqrt{n}(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0) \tag{S40}$$

$$\begin{aligned}
&= -\mathbf{H}^{-1}\mathbf{G} \\
&= -\{\mathbf{H}_0 + \mathbf{H}_1 + o_p(1)\}^{-1}\{\mathbf{G}_{00} + \mathbf{G}_{013}^T n^{1/2}\{\widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0^-\} + o_p(1)\} \\
&= -\{\mathbf{H}_0 + \mathbf{G}_{013}^T \mathbf{P} + o_p(1)\}^{-1}\{\mathbf{G}_{00} + \mathbf{G}_{013}^T \mathbf{L} + o_p(1)\} \\
&= O_p(1)
\end{aligned}$$

where \mathbf{L} is defined in Theorem 1.

Part II

Now note that we can write $\mathbf{P} = (\mathbf{P}_1, \dots, \mathbf{P}_{J-1})$, where \mathbf{P}_l is the l th column of \mathbf{P} , $l = 1, \dots, J-1$, which can be written as .

$$\begin{aligned}
\mathbf{P}_l = & \operatorname{argmin}_{\widetilde{\mathbf{P}}_l} E \left\{ \left(\int_0^1 X_{il}(t) \alpha_0(t) dt + \left[\int_0^1 \mathbf{B}_r(t)^T \boldsymbol{\Theta}_\gamma^T \widetilde{\mathbf{P}}_l \boldsymbol{\beta}_0^T \mathbf{X}_i(t) dt \right. \right. \right. \\
& \left. \left. \left. - E \left\{ \int_0^1 \mathbf{B}_r(t)^T \boldsymbol{\Theta}_\gamma^T \widetilde{\mathbf{P}}_l \boldsymbol{\beta}_0^T \mathbf{X}_i(t) dt \mid \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i) \right\} \right] \right)^2 \\
& \left. \times \partial[g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \mid \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] / \partial\{\boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \right\}.
\end{aligned}$$

Hence,

$$\begin{aligned}
& \mathbf{B}_r(\cdot)^T \boldsymbol{\Theta}_\gamma^T \mathbf{P}_l \\
= & \operatorname{argmin}_{\mathbf{B}_r(\cdot)^T \boldsymbol{\Theta}_\gamma^T \mathbf{P}_l} E \left\{ \left(\int_0^1 X_{il}(t) \alpha_0(t) dt + \left[\int_0^1 \mathbf{B}_r(t)^T \boldsymbol{\Theta}_\gamma^T \widetilde{\mathbf{P}}_l \boldsymbol{\beta}_0^T \mathbf{X}_i(t) dt \right. \right. \right. \\
& \left. \left. \left. - E \left\{ \int_0^1 \mathbf{B}_r(t)^T \boldsymbol{\Theta}_\gamma^T \widetilde{\mathbf{P}}_l \boldsymbol{\beta}_0^T \mathbf{X}_i(t) dt \mid \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i) \right\} \right] \right)^2 \\
& \left. \times \partial[g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \mid \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] / \partial\{\boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \right\}.
\end{aligned}$$

Now let $\delta_l \in C^q[0, 1]$, $\delta_l(0) = 1$ and

$$\begin{aligned}
& \delta_l(\cdot) \\
= & \operatorname{argmin}_{\widetilde{\delta}_l} E \left\{ \left(\int_0^1 X_{il}(t) \alpha_0(t) dt + \left[\int_0^1 \boldsymbol{\beta}_0^T \widetilde{\delta}_l(t) \mathbf{X}_{ic}(t) dt \right] \right)^2 \right. \quad (\text{S41}) \\
& \left. \times \Delta g_c^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \right\}
\end{aligned}$$

where recalling that $\Delta g_c^*\{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}$ is defined before Theorem 2, and $\mathbf{X}_{ic}(s) = \mathbf{X}_i(s) - E\{\mathbf{X}_i(s) \mid \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}$. We further define $\boldsymbol{\alpha}_{c0}(\mathbf{X}_i) = \boldsymbol{\alpha}_0(\mathbf{X}_i) -$

$E\{\boldsymbol{\alpha}_0(\mathbf{X}_i)|\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}$. As the number of spline knots goes to infinity, $\|\mathbf{B}_r(\cdot)^\top\boldsymbol{\Theta}_\gamma^\top\mathbf{P}_l-\delta_l(\cdot)\|_\infty=O_p(h_b^q)$. Hence

$$\begin{aligned} & \left\| \mathbf{G}_{013}^\top\mathbf{P}_l - E \left[\Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} \boldsymbol{\Theta}_\beta \boldsymbol{\alpha}_{c0}(\mathbf{X}_i) \int_0^1 \boldsymbol{\beta}_0^\top \mathbf{X}_{ic}(t) \delta_l(t) dt \right] \right\|_2 \\ &= o_p(1). \end{aligned} \quad (\text{S42})$$

Further, the Gâteaux derivative of the target function in (S41) at $\tilde{\delta}_l = \delta_l$ in the direction $\mathbf{w}_0^*(t)$ satisfies

$$\begin{aligned} \mathbf{0} &= \partial E \left(\int_0^1 X_{il}(t) \alpha_0(t) dt + \left[\int_0^1 \boldsymbol{\beta}_0^\top \mathbf{X}_{ic}(t) \{ \delta_l(t) + \mathbf{v}^\top \mathbf{w}_0^*(t) \} dt \right]^2 \right. \\ &\quad \left. \times \Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} / \partial \mathbf{v} \Big|_{\mathbf{v}=\mathbf{0}} \right) \\ &= 2E \left[\int_0^1 X_{il}(t) \alpha_0(t) dt \Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} \int_0^1 \boldsymbol{\beta}_0^\top \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \right] \\ &\quad + 2 \int_0^1 \delta_l(t) \boldsymbol{\Theta}_\beta E[\boldsymbol{\alpha}_{c0}(\mathbf{X}_i) \Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} \mathbf{X}_{ic}^\top(t)] \boldsymbol{\beta}_0 dt \\ &= 2E \left[\int_0^1 X_{icl}(t) \alpha_0(t) dt \Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} \int_0^1 \boldsymbol{\beta}_0^\top \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \right] \\ &\quad + 2 \int_0^1 \delta_l(t) \boldsymbol{\Theta}_\beta E[\boldsymbol{\alpha}_{c0}(\mathbf{X}_i) \Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} \mathbf{X}_{ic}^\top(t)] \boldsymbol{\beta}_0 dt, \end{aligned}$$

where $\mathbf{w}_0^*(t)$ is defined in (7), X_{icl} is the l th element of \mathbf{X}_{ic} . The second equality holds by the definition of $\mathbf{w}_0^*(t)$ in (7). The last equality holds because

$$\begin{aligned} & E \left[\int_0^1 E\{X_{il}(t)|\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0\} \alpha_0(t) dt \Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} \int_0^1 \boldsymbol{\beta}_0^\top \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \right] \\ &= \mathbf{0}. \end{aligned}$$

This implies

$$\begin{aligned} & E \left[\boldsymbol{\Theta}_\beta \boldsymbol{\alpha}_{c0}(\mathbf{X}_i) \Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} \int_0^1 \boldsymbol{\beta}_0^\top \mathbf{X}_{ic}(t) \delta_l(t) dt \right] \\ &= -E \left[\int_0^1 X_{icl}(t) \alpha_0(t) dt \Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} \int_0^1 \boldsymbol{\beta}_0^\top \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \right]. \end{aligned}$$

This holds for each $l = 1, \dots, J-1$. Combine this result with (S42), we have

$$\left\| \mathbf{G}_{013}^\top\mathbf{P} + E \left[\Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} \int_0^1 \boldsymbol{\beta}_0^\top \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \boldsymbol{\alpha}_{c0}(\mathbf{X}_i)^\top \boldsymbol{\Theta}_\beta^\top \right] \right\|_2$$

$$= o_p(1).$$

Next, by (S29) and (S30), where $\widehat{\mathbf{C}}_{\mathbf{Q}}(\boldsymbol{\beta}_0)$ and $\mathbf{C}_{\mathbf{Q}}(\boldsymbol{\beta}_0)$ in (S29) and (S30) are defined in (S25), we can write

$$n^{-1/2}\mathbf{L} = \widehat{\mathbf{L}}\{1 + o_p(1)\}, \quad (\text{S43})$$

where

$$\begin{aligned} \widehat{\mathbf{L}} &= \operatorname{argmin}_{\widetilde{\mathbf{L}}} n^{-1} \sum_{i=1}^n \left([g^*\{Y_i, \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right. \\ &\quad \left. \times \Delta g_c^*\{Y_i, \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\}^{-1} + \left[\int_0^1 \mathbf{B}_r(t)^{\text{T}} \boldsymbol{\Theta}_{\gamma}^{\text{T}} \widetilde{\mathbf{L}} \boldsymbol{\beta}_0^{\text{T}} \mathbf{X}_{ic}(t) dt \right]^2 \Delta g_c^*\{Y_i, \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \right]. \end{aligned}$$

Further, by above equality we have

$$\begin{aligned} &\mathbf{B}_r(\cdot)^{\text{T}} \boldsymbol{\Theta}_{\gamma}^{\text{T}} \widehat{\mathbf{L}} \\ &= \operatorname{argmin}_{\mathbf{B}_r(\cdot)^{\text{T}} \boldsymbol{\Theta}_{\gamma}^{\text{T}} \widetilde{\mathbf{L}}} n^{-1} \sum_{i=1}^n \left([g^*\{Y_i, \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right. \\ &\quad \left. \Delta g_c^*\{Y_i, \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\}^{-1} + \left[\int_0^1 \mathbf{B}_r(t)^{\text{T}} \boldsymbol{\Theta}_{\gamma}^{\text{T}} \widetilde{\mathbf{L}} \boldsymbol{\beta}_0^{\text{T}} \mathbf{X}_{ic}(t) dt \right]^2 \Delta g_c^*\{Y_i, \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \right]. \end{aligned}$$

Let

$$\begin{aligned} &\widehat{\eta}(\cdot) \quad (\text{S44}) \\ &= \operatorname{argmin}_{\widetilde{\eta}(\cdot)} n^{-1} \sum_{i=1}^n \left\{ \left([g^*\{Y_i, \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \right. \right. \\ &\quad \left. \left. - E\{g^*\{Y_i, \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \Delta g_c^*\{Y_i, \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\}^{-1} \right. \right. \\ &\quad \left. \left. + \left[\int_0^1 \widetilde{\eta}(t) \boldsymbol{\beta}_0^{\text{T}} \mathbf{X}_{ic}(t) dt \right]^2 \Delta g_c^*\{Y_i, \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \right\}. \end{aligned}$$

As the number of spline knots goes to infinity, $\|\mathbf{B}_r(\cdot)^{\text{T}} \boldsymbol{\Theta}_{\gamma}^{\text{T}} \widehat{\mathbf{L}}(\cdot) - \widehat{\eta}(\cdot)\|_{\infty} = O_p(h_b^q)$. Combining with (S43) we have

$$\begin{aligned} &\left\| \mathbf{G}_{013}^{\text{T}} \mathbf{L} - \int_0^1 E \left[\boldsymbol{\Theta}_{\beta} \boldsymbol{\alpha}_c(\mathbf{X}_i) \right. \right. \\ &\quad \left. \left. \Delta g_c^*\{Y_i, \boldsymbol{\beta}_0^{\text{T}} \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \boldsymbol{\beta}_0^{\text{T}} \mathbf{X}_{ic}(t) \right] n^{1/2} \widehat{\eta}(t) dt \right\|_{\infty} \\ &= o_p(1). \end{aligned} \quad (\text{S45})$$

Now taking the Gâteaux derivative of the target function in (S44) at $\hat{\eta}$ in the direction of $\mathbf{w}_0^*(t)$, we have

$$\begin{aligned}
\mathbf{0} &= \partial n^{-1} \sum_{i=1}^n \left[\left\{ (g^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\}) - E[g^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)] \right\} \right. \\
&\quad \left. \Delta g_c^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\}^{-1} + \int_0^1 \{\hat{\eta}(t) + \mathbf{v}^T \mathbf{w}_0^*(t)\} \beta_0^T \mathbf{X}_{ic}(t) dt \right\}^2 \\
&\quad \times \Delta g_c^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} \Big] / \partial \mathbf{v} |_{\mathbf{v}=\mathbf{0}} \\
&= 2n^{-1} \sum_{i=1}^n \left(\left[(g^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\}) - E[g^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)] \right] \right. \\
&\quad \times \Delta g_c^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\}^{-1} + \int_0^1 \hat{\eta}(t) \beta_0^T \mathbf{X}_{ic}(t) dt \Big] \\
&\quad \times \Delta g_c^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} \int_0^1 \beta_0^T \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \Big) \\
&= 2n^{-1} \sum_{i=1}^n \left\{ (g^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\}) - E[g^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)] \right\} \\
&\quad \times \int_0^1 \beta_0^T \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \Big\} + 2 \int_0^1 \hat{\eta}(t) E \left[\beta_0^T \mathbf{X}_{ic}(t) dt \right. \\
&\quad \times \Delta g_c^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} \int_0^1 \beta_0^T \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \Big] + o_p(n^{-1/2}) \\
&= 2n^{-1} \sum_{i=1}^n \left\{ (g^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\}) - E[g^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)] \right\} \\
&\quad \times \int_0^1 \beta_0^T \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \Big\} + 2 \left(\int_0^1 \hat{\eta}(t) \boldsymbol{\Theta}_\beta E[\alpha_{c0}(\mathbf{X}_i)] \right. \\
&\quad \times \Delta g_c^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} \mathbf{X}_{ic}^T(t) \Big] \beta_0 dt \Big) + o_p(n^{-1/2}).
\end{aligned}$$

The last equality holds by the definition of $\mathbf{w}_0^*(t)$. This implies

$$\begin{aligned}
&n^{-1} \sum_{i=1}^n \left([g^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\}) - E\{g^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)\}] \right. \\
&\quad \times \int_0^1 \beta_0^T \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \Big) \\
&= - \int_0^1 \hat{\eta}(t) \boldsymbol{\Theta}_\beta E[\alpha_{c0}(\mathbf{X}_i)] \Delta g_c^* \{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} \mathbf{X}_{ic}^T(t) \Big] \beta_0 dt \\
&\quad + o_p(n^{-1/2})
\end{aligned}$$

Combining with (S45), we have

$$\begin{aligned}
& \left\| \mathbf{G}_{013}^T \mathbf{L} + n^{-1/2} \sum_{i=1}^n \left([g^* \{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^* \{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \right. \right. \\
& \quad \left. \left. \times \int_0^1 \boldsymbol{\beta}_0^T \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \right) \right\|_2 \\
& = o_p(1).
\end{aligned}$$

As a result, by (S40) the population asymptotic forms of $\sqrt{n}(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0)$ can be written as

$$\begin{aligned}
& \sqrt{n}(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0) \\
& = -\{\mathbf{H}_0 + \mathbf{G}_{013}^T \mathbf{P} + o_p(1)\}^{-1} \{\mathbf{G}_{00} + \mathbf{G}_{013}^T \mathbf{L} + o_p(1)\} \\
& = -\left\{ \mathbf{H}_0 - E \left[\Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \int_0^1 \boldsymbol{\beta}_0^T \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \boldsymbol{\alpha}_{c0}(\mathbf{X}_i)^T \boldsymbol{\Theta}_\beta^T \right] \right. \\
& \quad \left. + o_p(1) \right\}^{-1} \left[\mathbf{G}_{00} - n^{-1/2} \sum_{i=1}^n \left\{ (g^* \{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \right. \right. \\
& \quad \left. \left. - E[g^* \{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)]) \int_0^1 \boldsymbol{\beta}_0^T \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \right\} + o_p(1) \right] \\
& = \mathbf{A}^{-1} \mathbf{B} + o_p(1),
\end{aligned}$$

where

$$\begin{aligned}
\mathbf{A} & = -\left(E[\Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \{\boldsymbol{\Theta}_\beta \boldsymbol{\alpha}_{c0}(\mathbf{X}_i)\}^{\otimes 2}] \right. \\
& \quad \left. - E \left[\Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \int_0^1 \boldsymbol{\beta}_0^T \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \boldsymbol{\alpha}_{c0}(\mathbf{X}_i)^T \boldsymbol{\Theta}_\beta^T \right] \right)
\end{aligned}$$

and

$$\begin{aligned}
\mathbf{B} & = n^{-1/2} [g^* \{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^* \{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \\
& \quad \times \left\{ \boldsymbol{\Theta}_\beta \boldsymbol{\alpha}_{c0}(\mathbf{X}_i) - \int_0^1 \boldsymbol{\beta}_0^T \mathbf{X}_{ic}(t) \mathbf{w}_0^*(t) dt \right\}.
\end{aligned}$$

If $g^* = g$, then $E\{g^* \{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} = 0$,
 $E[\Delta g_c^* \{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)] = -E[g^{*2} \{Y_i, \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^T \boldsymbol{\alpha}_0(\mathbf{X}_i)]$ and $\mathbf{w}_0^*(t) = \mathbf{w}_0(t)$ as defined in (S48). Hence we have

$$\sqrt{n}(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}) = \mathbf{A}_0^{-1} \mathbf{B}_0 + o_p(1)$$

where

$$\begin{aligned} \mathbf{A}_0 &= E[g^2\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}\{\boldsymbol{\Theta}_\beta \boldsymbol{\alpha}_{c0}(\mathbf{X}_i)\}^{\otimes 2}] \\ &\quad - E\left[g^2\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} \int_0^1 \boldsymbol{\beta}_0^\top \mathbf{X}_{ic}(t) \mathbf{w}_0(t) dt \boldsymbol{\alpha}_{c0}(\mathbf{X}_i)^\top \boldsymbol{\Theta}_\beta^\top\right] \end{aligned}$$

and

$$\begin{aligned} \mathbf{B}_0 &= n^{-1/2}[g\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]\left\{\boldsymbol{\Theta}_\beta \boldsymbol{\alpha}_{c0}(\mathbf{X}_i) - \int_0^1 \boldsymbol{\beta}_0^\top \mathbf{X}_{ic}(t) \mathbf{w}_0(t) dt\right\} \\ &= \mathbf{S}_{\text{oeff}}, \end{aligned}$$

where \mathbf{S}_{oeff} is defined in (S47). With simple calculation, we can see that $\mathbf{A}_0 = \text{var}(\mathbf{B}_0)$. Hence, when g^* is correctly specified, $\widehat{\boldsymbol{\beta}}$ is the efficient estimator. This proves the result. \square

S3.3 Proof of Theorem 3

Proof:

$$\begin{aligned} &\sup_{t \in [0,1]} |\mathbf{B}_r(t)^\top \widehat{\boldsymbol{\gamma}}(\widehat{\boldsymbol{\beta}}) - \alpha_0(t)| \\ &= \sup_{t \in [0,1]} |\mathbf{B}_r(t)^\top \boldsymbol{\Theta}_\gamma^\top \widehat{\boldsymbol{\gamma}}^-(\widehat{\boldsymbol{\beta}}) - \alpha_0(t)| \\ &\leq \sup_{t \in [0,1]} |\mathbf{B}_r(t)^\top \boldsymbol{\Theta}_\gamma^\top \widehat{\boldsymbol{\gamma}}^-(\widehat{\boldsymbol{\beta}}) - \mathbf{B}_r(t)^\top \boldsymbol{\Theta}_\gamma^\top \widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta}_0)| + \sup_{t \in [0,1]} |\mathbf{B}_r(t)^\top \boldsymbol{\Theta}_\gamma^\top \widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta}_0) - \mathbf{B}_r(t)^\top \boldsymbol{\Theta}_\gamma^\top \boldsymbol{\gamma}_0^-| \\ &\quad + \sup_{t \in [0,1]} |\mathbf{B}_r(t)^\top \boldsymbol{\gamma}_0 - \alpha_0(t)| \\ &\leq \|\widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta})/\partial \boldsymbol{\beta}^\top|_{\boldsymbol{\beta}=\boldsymbol{\beta}^*}(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0)\|_\infty + \|\widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0\|_\infty + O_p(h_b^q) \\ &= O_p(n^{-1/2}h_b^{-1/2} + h_b^q) + \|\widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0\|_\infty \\ &= O_p(n^{-1/2}h_b^{-1/2} + h_b^q) \\ &= O_p(n^{-1/2}h_b^{-1/2}). \end{aligned} \tag{S46}$$

The third line holds by Lemma 1 and Condition (A5). The fourth line holds because

$$\widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta})/\partial \boldsymbol{\beta}^\top|_{\boldsymbol{\beta}=\boldsymbol{\beta}^*}(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0) = \mathbf{P}_1 + o_p(\mathbf{P}_1)$$

by Lemma 4, where

$$\begin{aligned} \mathbf{P}_1 &= - \left(\left\{ E \left(\boldsymbol{\Theta}_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]^\top \boldsymbol{\beta}_0 \right. \right. \right. \\ &\quad \times \frac{\partial (g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E[g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)])}{\partial \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)} \\ &\quad \left. \left. \left. \times \boldsymbol{\beta}_0^\top [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \boldsymbol{\Theta}_\gamma^\top \right) \right\}^{-1} \right) \mathbf{M} (\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0). \end{aligned}$$

where

$$\begin{aligned} \mathbf{M} &= E(\boldsymbol{\Theta}_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]^\top \boldsymbol{\beta}_0 \boldsymbol{\alpha}_0(\mathbf{X}_i)^\top \boldsymbol{\Theta}_\beta^\top \\ &\quad \times \partial [g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] / \partial \{\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}) \end{aligned}$$

is a $d_{\gamma-1} \times d_\beta$ dimensional matrix. Now note that $\|\mathbf{P}_1\|_\infty \leq \|\mathbf{P}_1\|_2$ by the fact that the vector sup norm is less than its L_2 norm, we obtain

$$\begin{aligned} &\|\mathbf{P}_1\|_\infty \\ &\leq \left\| \left(\left\{ E \left(\boldsymbol{\Theta}_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]^\top \boldsymbol{\beta}_0 \right. \right. \right. \\ &\quad \times \frac{\partial (g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E[g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)])}{\partial \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)} \\ &\quad \left. \left. \left. \times \boldsymbol{\beta}_0^\top [\mathbf{Z}_i - E\{\mathbf{Z}_i | \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \boldsymbol{\Theta}_\gamma^\top \right) \right\}^{-1} \right\|_2 \|\mathbf{M}\|_2 \|(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0)\|_2 \\ &= O_p(h_b^{-1}) O_p(h_b^{1/2}) O_p(n^{-1/2}) \\ &= O_p(n^{-1/2} h_b^{-1/2}). \end{aligned}$$

The second to the last equality holds because of (S55) and the root n convergence of $\widehat{\boldsymbol{\beta}}$. In addition, $\|\mathbf{M}\|_2 = O_p(h_b^{1/2})$ by (S56).

The fifth equality in (S46) holds because by choosing \mathbf{a} to be a unit vector with 1 at one entry in Theorem 1, we can obtain that each entry of $\widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0$ is of order $O_p(n^{-1/2} h_b^{-1/2})$, and thus $\|\widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}_0) - \boldsymbol{\gamma}_0\|_\infty = O_p(n^{-1/2} h_b^{-1/2})$. The last equality in (S46) holds by Condition (A4). \square

S4 Necessary propositions and lemmas

Proposition S4.1. *The efficient score function of model (2) is $\mathbf{S}_{\text{eff}} = (\mathbf{S}_{\text{eff}\beta}^T, \mathbf{S}_{\text{eff}\gamma}^T)^T$, where*

$$\begin{aligned}\mathbf{S}_{\text{eff}\beta} &= \frac{f'_2(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})}{f(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})} (\mathbf{I}_{J-1}, \mathbf{0}) \{\mathbf{Z} - E(\mathbf{Z} \mid \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})\} \boldsymbol{\gamma}, \\ \mathbf{S}_{\text{eff}\gamma} &= \frac{f'_2(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})}{f(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})} (\mathbf{0}, \mathbf{I}_{d_\gamma-1}) \{\mathbf{Z} - E(\mathbf{Z} \mid \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})\}^T \boldsymbol{\beta}.\end{aligned}$$

Here f'_2 stands for the derivative of f with respect to the second variable.

Proof: We first calculate the score vector $\mathbf{S} = (\mathbf{S}_\beta^T, \mathbf{S}_\gamma^T)^T$. Taking derivative of the log likelihood of one observation with respect to the parameters in $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, we obtain

$$\begin{aligned}\mathbf{S}_\beta &= \frac{f'_2(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})}{f(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})} (\mathbf{I}_{J-1}, \mathbf{0}) \mathbf{Z} \boldsymbol{\gamma}, \\ \mathbf{S}_\gamma &= \frac{f'_2(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})}{f(Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})} (\mathbf{0}, \mathbf{I}_{d_\gamma-1}) \mathbf{Z}^T \boldsymbol{\beta}.\end{aligned}$$

We first show that $\mathbf{S}_{\text{eff}} \in \Lambda^\perp$. This is verified by noting that

$$\mathbf{S}_{\text{eff}} = \mathbf{S} - E(\mathbf{S} \mid Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}),$$

and \mathbf{S} satisfies $E(\mathbf{S} \mid \mathbf{Z}) = \mathbf{0} = E(\mathbf{S} \mid \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma})$. In addition, we also have $E(\mathbf{S} \mid Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}) \in \Lambda_f \subset \Lambda$ since $E\{E(\mathbf{S} \mid Y, \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}) \mid \boldsymbol{\beta}^T \mathbf{Z} \boldsymbol{\gamma}\} = \mathbf{0}$. \square

Proposition S4.2. *Under model (1), the efficient score function for $\boldsymbol{\beta}$ is*

$$\mathbf{S}_{\text{oeff}} = g\{Y, \boldsymbol{\beta}^T \boldsymbol{\alpha}(\mathbf{X})\} \left\{ \boldsymbol{\Theta}_\beta \boldsymbol{\alpha}_c(\mathbf{X}) - \int_0^1 \boldsymbol{\beta}^T \mathbf{X}_c(t) \mathbf{w}_0(t) dt \right\} \quad (\text{S47})$$

where $\mathbf{w}_0(t)$ is a $(J-1)$ -dimensional function that satisfies

$$\begin{aligned}\boldsymbol{\Theta}_\beta E[\boldsymbol{\alpha}_c(\mathbf{X}) g^2\{Y, \boldsymbol{\beta}^T \boldsymbol{\alpha}(\mathbf{X})\} \mathbf{X}_c^T(t)] \boldsymbol{\beta} \\ = \int_0^1 E[\boldsymbol{\beta}^T \mathbf{X}_c(s) g^2\{Y, \boldsymbol{\beta}^T \boldsymbol{\alpha}(\mathbf{X})\} \mathbf{X}_c^T(t) \boldsymbol{\beta}] \mathbf{w}_0(s) ds.\end{aligned} \quad (\text{S48})$$

Here we use the subindex o to indicate quantities calculated under the original model (1).

Proof: We first make the observation that Λ^\perp is the nuisance tangent space orthogonal complement of the B-spline approximated model (2). Follow the same arguments as those lead to Proposition 3, it can be shown that the spaces corresponding to Λ_x, Λ_f for model (1) are

$$\begin{aligned}\Lambda_{ox} &= [\mathbf{f} \{ \mathbf{X}(t) \} : \forall \mathbf{f} \text{ such that } E(\mathbf{f}) = \mathbf{0}], \\ \Lambda_{of} &= [\mathbf{f} \{ Y, \boldsymbol{\beta}^\top \boldsymbol{\alpha}(\mathbf{X}) \} : \forall \mathbf{f} \text{ such that } E\{\mathbf{f} \mid \mathbf{X}(t)\} = E\{\mathbf{f} \mid \boldsymbol{\beta}^\top \boldsymbol{\alpha}(\mathbf{X})\} = \mathbf{0}].\end{aligned}$$

In addition, the nuisance tangent space with respect to $\alpha(t)$ is

$$\tilde{\Lambda}_{o\alpha} = \left[g \{ Y, \boldsymbol{\beta}^\top \boldsymbol{\alpha}(\mathbf{X}) \} \int_0^1 \boldsymbol{\beta}^\top \mathbf{X}(t) \mathbf{w}(t) dt : \forall \mathbf{w}(t) \in \mathcal{R}^{J-1} \right].$$

After projecting $\tilde{\Lambda}_{o\alpha}$ to Λ_{ox} and Λ_{of} to get the residual, we obtain

$$\begin{aligned}\Lambda_{o\alpha} &\equiv \tilde{\Lambda}_{o\alpha} - \Pi(\tilde{\Lambda}_{o\alpha} \mid \Lambda_{ox} + \Lambda_{of}) \\ &= \left[g \{ Y, \boldsymbol{\beta}^\top \boldsymbol{\alpha}(\mathbf{X}) \} \int_0^1 \boldsymbol{\beta}^\top \mathbf{X}_c(t) \mathbf{w}(t) dt : \forall \mathbf{w}(t) \in \mathcal{R}^{J-1} \right].\end{aligned}$$

We can easily see that with respect to the model in (1), the nuisance tangent space is $\Lambda = \Lambda_{ox} \oplus \Lambda_{of} \oplus \Lambda_{o\alpha}$.

We can see that the score function with respect to the parameters in $\boldsymbol{\beta}$ is

$$\begin{aligned}\mathbf{S}_{o\beta} &= g\{Y, \boldsymbol{\beta}^\top \boldsymbol{\alpha}(\mathbf{X})\} \boldsymbol{\Theta}_\beta \boldsymbol{\alpha}(\mathbf{X}) \\ &= g\{Y, \boldsymbol{\beta}^\top \boldsymbol{\alpha}(\mathbf{X})\} \left\{ \boldsymbol{\Theta}_\beta \boldsymbol{\alpha}_c(\mathbf{X}) - \int_0^1 \boldsymbol{\beta}^\top \mathbf{X}_c(t) \mathbf{w}_0(t) dt \right\} \\ &\quad + g\{Y, \boldsymbol{\beta}^\top \boldsymbol{\alpha}(\mathbf{X})\} \int_0^1 \boldsymbol{\beta}^\top \mathbf{X}_c(t) \mathbf{w}_0(t) dt \\ &\quad + g\{Y, \boldsymbol{\beta}^\top \boldsymbol{\alpha}(\mathbf{X})\} \boldsymbol{\Theta}_\beta E\{\boldsymbol{\alpha}(\mathbf{X}) \mid \boldsymbol{\beta}^\top \boldsymbol{\alpha}(\mathbf{X})\},\end{aligned}$$

where the second and third summands of $\mathbf{S}_{o\beta}$ belong to $\Lambda_{o\alpha}$ and Λ_{of} respectively. We can also verify that the first summand of $\mathbf{S}_{o\beta}$ is simultaneously orthogonal to $\Lambda_{ox}, \Lambda_{of}$ and $\Lambda_{o\alpha}$, hence the efficient score of model (1) is indeed as given in (S47). \square

Lemma 1. *There is a constant $D_r > 0$ such that for each spline $\sum_{k=1}^{d_\gamma} c_k B_{rk}$, and for each $1 \leq p \leq \infty$*

$$D_r \|\mathbf{c}'\|_p \leq \left\| \sum_{k=1}^{d_\gamma} c_k B_{rk} \right\|_p \leq \|\mathbf{c}'\|_p,$$

where $\mathbf{c}' = \{c_k\{(t_k - t_{k-r})/r\}^{1/p}, k = 1, \dots, d_\gamma\}^T$.

Proof: This is a direct consequence of Theorem 5.4.2 on page 145 in DeVore and Lorentz (1993). \square

Lemma 2. *Let \mathbf{u} be a d_γ -dimensional vector with $\|\mathbf{u}\|_2 = 1$. There exist positive constants D_1, D_2, D_3, D_4 such that*

$$\begin{aligned} D_1 h_b &\leq \mathbf{u}^T \mathbf{C}(\boldsymbol{\beta}) \mathbf{u} \leq D_2 h_b, \\ D_2^{-1} h_b^{-1} &\leq \mathbf{u}^T \mathbf{C}(\boldsymbol{\beta})^{-1} \mathbf{u} \leq D_1^{-1} h_b^{-1}, \end{aligned}$$

and

$$\begin{aligned} D_3 h_b &\leq \mathbf{u}^T \widehat{\mathbf{C}}(\boldsymbol{\beta}) \mathbf{u} \leq D_4 h_b, \\ D_4^{-1} h_b^{-1} &\leq \mathbf{u}^T \widehat{\mathbf{C}}(\boldsymbol{\beta})^{-1} \mathbf{u} \leq D_3^{-1} h_b^{-1} \end{aligned}$$

in probability.

Proof: First note that by the Cauchy-Schwartz inequality, Lemma 1 and Condition (A6), we have

$$\begin{aligned} &E \left[\left\{ \mathbf{u}^T \int_0^1 \mathbf{B}_r(t) \boldsymbol{\beta}^T \mathbf{X}(t) dt \right\}^2 \right] \\ &\leq E \left[\int_0^1 \left\{ \sum_{k=1}^{d_\gamma} u_k B_{rk}(t) \right\}^2 dt \int_0^1 \{\boldsymbol{\beta}^T \mathbf{X}(t)\}^2 dt \right] \\ &= \int_0^1 \left\{ \sum_{k=1}^{d_\gamma} u_k B_{rk}(t) \right\}^2 dt E \left\{ \int_0^1 \{\boldsymbol{\beta}^T \mathbf{X}(t)\}^2 dt \right\} \\ &\leq \|\mathbf{u}'\|_2^2 O(1) \\ &= O(h_b), \end{aligned}$$

where $\mathbf{u}' = \{u_k\{(t_k - t_{k-r})/r\}^{1/2}, k = 1, \dots, d_\gamma\}^T$, whose L_2 norm is of order $O(h_b^{1/2})$. Thus we have $\mathbf{u}^T \mathbf{C}(\boldsymbol{\beta}) \mathbf{u} \leq D_2 h_b$ for some positive constant $D_2 < \infty$.

As shown in (28) in Cardot et al. (2003), since the eigenvalues of the covariance operator $\Gamma(\boldsymbol{\beta})$ are strictly positive, there is a positive constant D such that

$$\langle \Gamma(\boldsymbol{\beta}) \phi, \phi \rangle \geq D \|\phi\|^2, \text{ for } \phi \in \mathcal{H}.$$

Note that $\mathbf{B}_r^T \mathbf{u} \in \mathcal{H}$, so we have

$$\mathbf{u}^T \mathbf{C}(\boldsymbol{\beta}) \mathbf{u} = \langle \Gamma(\boldsymbol{\beta}) \mathbf{B}_r^T \mathbf{u}, \mathbf{B}_r^T \mathbf{u} \rangle \geq D \|\mathbf{B}_r^T \mathbf{u}\|_2 \geq D_1 \|\mathbf{u}\|^2 h_b = D_1 h_b$$

for a positive constant D_1 by Lemma 1 and Condition (A4). Therefore, $D_1 h_b \leq \mathbf{u}^T \mathbf{C}(\boldsymbol{\beta}) \mathbf{u} \leq D_2 h_b$. And so $D_2^{-1} h_b^{-1} \leq \mathbf{u}^T \mathbf{C}^{-1}(\boldsymbol{\beta}) \mathbf{u} \leq D_1^{-1} h_b^{-1}$. Further, with Theorem 1.19 in Chatelin (1983), we have

$$\|\widehat{\mathbf{C}}(\boldsymbol{\beta}) - \mathbf{C}(\boldsymbol{\beta})\|_2 \leq \sup_{1 \leq l \leq d_\gamma} \sum_{k=1}^{d_\gamma} \|\Gamma_n - \Gamma\|_2 | \langle B_{rk}, B_{rl} \rangle |$$

As shown in Cardot et al. (2003), Lemma 5.3 in Cardot et al. (1999) implies $\|\Gamma_n - \Gamma\|_2 = o_p(n^{(h_b-1)/2})$. Further, by the property of B-spline basis, we have when $|k - l| > r$, $B_{rk} B_{rl} = 0$. Therefore, $\sup_{1 \leq l \leq d_\gamma} \sum_{k=1}^{d_\gamma} | \langle B_{rk}, B_{rl} \rangle | = O(h_b)$, which implies

$$\|\widehat{\mathbf{C}}(\boldsymbol{\beta}) - \mathbf{C}(\boldsymbol{\beta})\|_2 \leq o_p(h_b n^{(h_b-1)/2}). \quad (\text{S49})$$

Now because $h_b < 1$, combine with the result that $D_1 h_b \leq \mathbf{u}^T \mathbf{C} \mathbf{u} \leq D_2 h_b$, by the triangular inequality we obtain

$$\begin{aligned} \mathbf{u}^T \widehat{\mathbf{C}}(\boldsymbol{\beta}) \mathbf{u} &= \mathbf{u}^T \mathbf{C}(\boldsymbol{\beta}) \mathbf{u} + \mathbf{u}^T \{\widehat{\mathbf{C}}(\boldsymbol{\beta}) - \mathbf{C}(\boldsymbol{\beta})\} \mathbf{u} \\ &\leq D_2 h_b + \|\mathbf{u}\|_2 \|\{\widehat{\mathbf{C}}(\boldsymbol{\beta}) - \mathbf{C}(\boldsymbol{\beta})\} \mathbf{u}\|_2 \\ &\leq D_2 h_b + \|\{\widehat{\mathbf{C}}(\boldsymbol{\beta}) - \mathbf{C}(\boldsymbol{\beta})\}\|_2 \|\mathbf{u}\|_2 \\ &= D_2 h_b + o_p(h_b) \end{aligned}$$

and

$$\begin{aligned} \mathbf{u}^T \widehat{\mathbf{C}}(\boldsymbol{\beta}) \mathbf{u} &= \mathbf{u}^T \mathbf{C}(\boldsymbol{\beta}) \mathbf{u} + \mathbf{u}^T \{\widehat{\mathbf{C}}(\boldsymbol{\beta}) - \mathbf{C}(\boldsymbol{\beta})\} \mathbf{u} \\ &\geq D_1 h_b - \|\mathbf{u}\|_2 \|\{\widehat{\mathbf{C}}(\boldsymbol{\beta}) - \mathbf{C}(\boldsymbol{\beta})\} \mathbf{u}\|_2 \\ &\geq D_1 h_b - \|\{\widehat{\mathbf{C}}(\boldsymbol{\beta}) - \mathbf{C}(\boldsymbol{\beta})\}\|_2 \|\mathbf{u}\|_2 \\ &= D_1 h_b + o_p(h_b). \end{aligned}$$

Thus, $D_3 h_b \leq \mathbf{u}^T \widehat{\mathbf{C}}(\boldsymbol{\beta}) \mathbf{u} \leq D_4 h_b$ in probability for some positive constant $D_3, D_4 < \infty$. And so $D_4^{-1} h_b \leq \mathbf{u}^T \widehat{\mathbf{C}}(\boldsymbol{\beta})^{-1} \mathbf{u} \leq D_3^{-1} h_b^{-1}$ in probability. This proves the result. \square

The result in Lemma 2 can be generalized to any vector valued random function with almost surely bounded L_2 norm and positive definite second moment operator. Therefore, we have the following corollary.

Corollary 1. *Let $\mathbf{Q}_i(t)$ be a d_q -dimensional vector valued random function with bounded L_2 norm, and let \mathbf{v} be an arbitrary d_q -dimensional vector. Let $\Gamma_{\mathbf{Q}}(\mathbf{v})$ be the second moment operator generated by $\mathbf{v}^T \mathbf{Q}_i(\cdot)$, i.e., $\Gamma_{\mathbf{Q}}(\mathbf{v})\phi(t) = E\{\langle \mathbf{v}^T \mathbf{Q}_i, \phi \rangle \mathbf{v}^T \mathbf{Q}_i(t)\}$. Assume $\Gamma_{\mathbf{Q}}(\mathbf{v})$ is strictly positive definite. We define the matrix $\mathbf{C}_{\mathbf{Q}}(\mathbf{v})$ to be a $d_\gamma \times d_\gamma$ matrix with its (k, l) element*

$$E\left\{\int_0^1 B_{rk}(t)\mathbf{v}^T \mathbf{Q}_i(t)dt \int_0^1 B_{rl}(t)\mathbf{v}^T \mathbf{Q}_i(t)dt\right\},$$

and $\widehat{\mathbf{C}}_{\mathbf{Q}}(\mathbf{v})$ to be a $d_\gamma \times d_\gamma$ matrix with its (k, l) element

$$n^{-1} \sum_{i=1}^n \int_0^1 B_{rk}(t)\mathbf{v}^T \mathbf{Q}_i(t)dt \int_0^1 B_{rl}(t)\mathbf{v}^T \mathbf{Q}_i(t)dt.$$

Let \mathbf{u} be a d_γ -dimensional vector with $\|\mathbf{u}\|_2 = 1$. Then there are positive constants D_5, D_6, D_7, D_8 such that

$$\begin{aligned} D_5 h_b &\leq \mathbf{u}^T \mathbf{C}_{\mathbf{Q}}(\mathbf{v}) \mathbf{u} \leq D_6 h_b, \\ D_6^{-1} h_b^{-1} &\leq \mathbf{u}^T \mathbf{C}_{\mathbf{Q}}^{-1}(\mathbf{v}) \mathbf{u} \leq D_5^{-1} h_b^{-1}, \end{aligned}$$

and

$$\begin{aligned} D_7 h_b &\leq \mathbf{u}^T \widehat{\mathbf{C}}_{\mathbf{Q}}(\mathbf{v}) \mathbf{u} \leq D_8 h_b, \\ D_8^{-1} h_b^{-1} &\leq \mathbf{u}^T \widehat{\mathbf{C}}_{\mathbf{Q}}^{-1}(\mathbf{v}) \mathbf{u} \leq D_7^{-1} h_b^{-1}, \end{aligned}$$

in probability. And

$$\|\widehat{\mathbf{C}}_{\mathbf{Q}}(\mathbf{v}) - \mathbf{C}_{\mathbf{Q}}(\mathbf{v})\|_2 \leq o_p(h_b n^{(h_b-1)/2}).$$

The proof of Corollary 1 follows the same arguments as those in the proof of Lemma 2 hence is omitted.

Lemma 3. Assume $C_i(\cdot)$ is a continuous random function of $t \in [0, 1]$. At each t , $|E\{C_i(t)\}| < \infty$. $\|C_i(\cdot)\|_2 < \infty$ a.s.. Then

$$|n^{-1} \sum_{i=1}^n \int_0^1 B_{rk}(t) C_i(t) dt| = O_p(h_b)$$

if $E\{C_i(t)\} \neq 0$ and

$$|n^{-1} \sum_{i=1}^n \int_0^1 B_{rk}(t) C_i(t) dt| = O_p\{\sqrt{h_b n^{-1} \log(n)}\}$$

if $E\{C_i(t)\} = 0$.

Proof: By the Bernstein's inequality in Bosq (1998), we have

$$\begin{aligned} & \left| 1/n \sum_{i=1}^n \int_0^1 B_{rk}(t) C_i(t) dt - E \left\{ \int_0^1 B_{rk}(t) C_i(t) dt \right\} \right| \\ &= O_p \left[\left[\sum_{i=1}^n E \left\{ 1/n \int_0^1 B_{rk}(t) C_i(t) dt \right\}^2 \log n \right]^{1/2} \right] \\ &= O_p\{\sqrt{h_b n^{-1} \log(n)}\}. \end{aligned}$$

The last equality holds from Corollary 1, by choosing $\mathbf{v}^T \mathbf{Q}_i(t) = C_i(t)$ and setting \mathbf{u} with $u_k = 1$ and $u_l = 0$, for $l \neq k$. Now if $E\{C_i(t)\} \neq 0$, then because B_{rk} is positive in the interval (t_{k-r}, t_k) , and is 0 otherwise (page 88 in De Boor (1978))

$$\begin{aligned} \left| E \left\{ \int_0^1 B_{rk}(t) C_i(t) dt \right\} \right| &= \left| \int_0^1 B_{rk}(t) E\{C_i(t)\} dt \right| \\ &= |E\{C_i(\xi)\} \int_0^1 B_{rk}(t) dt| \\ &= |E\{C_i(\xi)\}| \int_0^1 B_{rk}(t) dt \\ &\leq D_9(t_k - t_{k-r}) \\ &= O_p(h_b). \end{aligned} \tag{S50}$$

where ξ is a point in the interval $[0, 1]$, D_9 is a finite constant. The second equality holds by the assumption that $C_i(\cdot)$ is continuous function in t and

the mean value theorem. The inequality holds because the support of B_{rk} is the interval (t_{k-r}, t_k) and $|E\{C_i(t)\}| < \infty$ for any $t \in [0, 1]$. Therefore, by Condition (A4) that $N^{-1}n(\log n)^{-1} \rightarrow \infty$ we have

$$\|n^{-1} \sum_{i=1}^n \int_0^1 B_{rk}(t)C_i(t)dt\|_2 = O_p(h_b)$$

for $E\{C_i(t)\} \neq 0$ and

$$\|n^{-1} \sum_{i=1}^n \int_0^1 B_{rk}(t)C_i(t)dt\|_2 = \sqrt{h_b n^{-1} \log(n)}$$

for $E\{C_i(t)\} = 0$. This proves the results. \square

Lemma 4. Assume $\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0 = o_p(1)$. Then

$$\begin{aligned} & \widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta})/\partial\boldsymbol{\beta}^\top|_{\boldsymbol{\beta}^*} \\ = & - \left(\left\{ E \left(\boldsymbol{\Theta}_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i|\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]^\top \boldsymbol{\beta}_0 \right. \right. \right. \\ & \times \frac{\partial (g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E[g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}|\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)])}{\partial \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)} \\ & \times \boldsymbol{\beta}_0^\top [\mathbf{Z}_i - E\{\mathbf{Z}_i|\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \boldsymbol{\Theta}_\gamma^\top \left. \right\}^{-1} \left\{ E(\boldsymbol{\Theta}_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i|\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}])^\top \right. \\ & \times \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)^\top \frac{\partial [g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}|\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}]}{\partial \{\boldsymbol{\beta}_0^\top \boldsymbol{\alpha}_0(\mathbf{X}_i)\}} \left. \right\} \\ & \times \{1 + o_p(1)\}, \end{aligned}$$

where $\boldsymbol{\beta}^*$ is a point on the line connecting $\widehat{\boldsymbol{\beta}}, \boldsymbol{\beta}_0$. In addition, $\|\widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta})/\partial\boldsymbol{\beta}^\top|_{\boldsymbol{\beta}=\boldsymbol{\beta}^*}\|_2 = O_p(h_b^{-1/2})$.

Proof: $\widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta})$ satisfies

$$\begin{aligned} & \sum_{i=1}^n \widehat{\mathbf{S}}_{\text{eff}\gamma} \{Y_i, \mathbf{Z}_i, \boldsymbol{\beta}, \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}), g^*\} \\ = & \sum_{i=1}^n \left\{ g^*\{Y_i, \boldsymbol{\beta}^\top \mathbf{Z}_i \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta})\} - \frac{\sum_{j=1}^J K_h \{\boldsymbol{\beta}^\top \mathbf{Z}_j \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) - \boldsymbol{\beta}^\top \mathbf{Z}_i \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta})\} g^*\{Y_j, \boldsymbol{\beta}^\top \mathbf{Z}_j \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta})\}}{\sum_{j=1}^J K_h \{\boldsymbol{\beta}^\top \mathbf{Z}_j \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) - \boldsymbol{\beta}^\top \mathbf{Z}_i \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta})\}} \right\} \\ & \boldsymbol{\Theta}_\gamma \left\{ \mathbf{Z}_i - \frac{\sum_{j=1}^J K_h \{\boldsymbol{\beta}^\top \mathbf{Z}_j \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) - \boldsymbol{\beta}^\top \mathbf{Z}_i \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta})\} \mathbf{Z}_j}{\sum_{j=1}^J K_h \{\boldsymbol{\beta}^\top \mathbf{Z}_j \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta}) - \boldsymbol{\beta}^\top \mathbf{Z}_i \widehat{\boldsymbol{\gamma}}(\boldsymbol{\beta})\}} \right\}^\top \boldsymbol{\beta} \end{aligned}$$

Further, the convergence of β^* implies $\sup_{t \in [0,1]} \{\mathbf{B}_r(t)^\top \widehat{\gamma}(\beta^*) - \mathbf{B}_r(t)^\top \widehat{\gamma}(\beta_0)\} = o_p(1)$, and thus $\sup_{t \in [0,1]} \{\mathbf{B}_r(t)^\top \widehat{\gamma}(\beta^*) - \alpha_0(t)\} = o_p(1)$. Now by the uniform convergence of the kernel estimator, and the consistency of $\mathbf{B}_r(\cdot)^\top \widehat{\gamma}(\beta^*)$ and β^* , \mathbf{U} is asymptotic equivalent to $-\mathbf{T}^{-1}$, where \mathbf{T} is defined in (S22), and in turn

$$\begin{aligned}
\mathbf{U} &= -\mathbf{T}_{00}^{-1} + o_p(\mathbf{T}_{00}^{-1}) \\
&= -\left(\left\{ E \left(\Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0 \alpha_0(\mathbf{X}_i)\}]^\top \beta_0 \right. \right. \right. \\
&\quad \times \frac{\partial (g^* \{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} - E[g^* \{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)])}{\partial \beta_0^\top \alpha_0(\mathbf{X}_i)} \\
&\quad \times \beta_0^\top [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma^\top \left. \right\}^{-1} \\
&\quad + o_p \left[\left\{ E \left(\Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0 \alpha_0(\mathbf{X}_i)\}]^\top \beta_0 \right. \right. \right. \\
&\quad \times \frac{\partial (g^* \{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} - E[g^* \{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)])}{\partial \beta_0^\top \alpha_0(\mathbf{X}_i)} \\
&\quad \times \beta_0^\top [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma^\top \left. \right\}^{-1} \left. \right]. \tag{S51}
\end{aligned}$$

Also, use the similar argument as those led to (S51), we have

$$\begin{aligned}
\mathbf{V} &= n^{-1} \sum_{i=1}^n \partial [g^* \{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} \\
&\quad - E\{g^* \{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}]^\top \beta_0 / \partial \beta^\top \\
&\quad + o_p \left(n^{-1} \sum_{i=1}^n \partial [g^* \{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} \right. \\
&\quad \left. - E\{g^* \{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}]^\top \beta_0 / \partial \beta^\top \right) \\
&= n^{-1} \sum_{i=1}^n \Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}]^\top \beta_0 \alpha_0(\mathbf{X}_i)^\top \\
&\quad \times \partial [g^* \{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} - E\{g^* \{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] / \partial \{\beta_0^\top \alpha_0(\mathbf{X}_i)\} \\
&\quad + o_p \left(n^{-1} \sum_{i=1}^n \Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^\top \alpha_0(\mathbf{X}_i)\}]^\top \beta_0 \alpha_0(\mathbf{X}_i)^\top \right. \\
&\quad \left. \times \partial [g^* \{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} - E\{g^* \{Y_i, \beta_0^\top \alpha_0(\mathbf{X}_i)\} | \beta_0^\top \alpha_0(\mathbf{X}_i)\}] / \partial \{\beta_0^\top \alpha_0(\mathbf{X}_i)\} \right).
\end{aligned}$$

Therefore, we can write

$$\begin{aligned}
& \widehat{\gamma}^-(\boldsymbol{\beta})/\partial\boldsymbol{\beta}^\top|_{\boldsymbol{\beta}^*} \\
= & -\left(\left\{E\left(\boldsymbol{\Theta}_\gamma[\mathbf{Z}_i - E\{\mathbf{Z}_i|\boldsymbol{\beta}_0\boldsymbol{\alpha}_0(\mathbf{X}_i)]\right]^\top\boldsymbol{\beta}_0\right.\right. \\
& \times \frac{\partial(g^*\{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E[g^*\{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}|\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)])}{\partial\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)} \\
& \left.\left.\times\boldsymbol{\beta}_0^\top[\mathbf{Z}_i - E\{\mathbf{Z}_i|\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}]\boldsymbol{\Theta}_\gamma^\top\right\}^{-1}\right)\left(n^{-1}\sum_{i=1}^n\boldsymbol{\Theta}_\gamma[\mathbf{Z}_i - E\{\mathbf{Z}_i|\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}]\right)^\top \\
& \boldsymbol{\beta}_0\boldsymbol{\alpha}_0(\mathbf{X}_i)^\top\partial[g^*\{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}|\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \\
& / \partial\{\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\})\{1 + o_p(1)\} \\
= & -\left(\left\{E\left(\boldsymbol{\Theta}_\gamma[\mathbf{Z}_i - E\{\mathbf{Z}_i|\boldsymbol{\beta}_0\boldsymbol{\alpha}_0(\mathbf{X}_i)]\right]^\top\boldsymbol{\beta}_0\right.\right. \\
& \times \frac{\partial(g^*\{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E[g^*\{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}|\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)])}{\partial\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)} \\
& \left.\left.\times\boldsymbol{\beta}_0^\top[\mathbf{Z}_i - E\{\mathbf{Z}_i|\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}]\boldsymbol{\Theta}_\gamma^\top\right\}^{-1}\right)\left\{E(\boldsymbol{\Theta}_\gamma[\mathbf{Z}_i - E\{\mathbf{Z}_i|\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}])^\top\right. \\
& \times\boldsymbol{\beta}_0\boldsymbol{\alpha}_0(\mathbf{X}_i)^\top\partial[g^*\{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}|\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}] \\
& \left.\left./\partial\{\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}\right\}\{1 + o_p(1)\}.
\end{aligned}$$

Now we can write

$$\partial\widehat{\gamma}^-(\boldsymbol{\beta})/\partial\boldsymbol{\beta}^\top|_{\boldsymbol{\beta}=\boldsymbol{\beta}^*} = \mathbf{P} + o_p(\mathbf{P}), \quad (\text{S52})$$

where

$$\begin{aligned}
\mathbf{P} = & -\left(\left\{E\left(\boldsymbol{\Theta}_\gamma[\mathbf{Z}_i - E\{\mathbf{Z}_i|\boldsymbol{\beta}_0\boldsymbol{\alpha}_0(\mathbf{X}_i)]\right]^\top\boldsymbol{\beta}_0\right.\right. \\
& \times \frac{\partial(g^*\{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\} - E[g^*\{Y_i, \boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}|\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)])}{\partial\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)} \\
& \left.\left.\times\boldsymbol{\beta}_0^\top[\mathbf{Z}_i - E\{\mathbf{Z}_i|\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}]\boldsymbol{\Theta}_\gamma^\top\right\}^{-1}\right)\mathbf{M},
\end{aligned} \quad (\text{S53})$$

where

$$\mathbf{M} = E(\boldsymbol{\Theta}_\gamma[\mathbf{Z}_i - E\{\mathbf{Z}_i|\boldsymbol{\beta}_0^\top\boldsymbol{\alpha}_0(\mathbf{X}_i)\}]^\top\boldsymbol{\beta}_0\boldsymbol{\alpha}_0(\mathbf{X}_i)^\top\boldsymbol{\Theta}_\beta^\top)$$

$$\times \partial[g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} - E\{g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)\}] / \partial\{\beta_0^T \alpha_0(\mathbf{X}_i)\}$$

is a $(d_{\gamma-1} \times J)$ -dimensional matrix. We further have

$$\begin{aligned} & \|\mathbf{P}\|_2 \\ \leq & \left\| \left(\left\{ E \left(\Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}]^T \beta_0 \right. \right. \right. \\ & \times \frac{\partial (g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} - E[g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)])}{\partial \beta_0^T \alpha_0(\mathbf{X}_i)} \\ & \left. \left. \left. \times \beta_0^T [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma^T \right\}^{-1} \right) \right\|_2 \|\mathbf{M}\|_2 \\ = & O_p(h_b^{-1}) O_p(h_b^{1/2}) \\ = & O_p(h_b^{-1/2}). \end{aligned} \tag{S54}$$

The second to the last equality holds because of the root n convergence of $\widehat{\beta}$, and because

$$\begin{aligned} & \left\| \left(\left\{ E \left(\Theta_\gamma [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}]^T \beta_0 \right. \right. \right. \\ & \times \frac{\partial (g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} - E[g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)])}{\partial \beta_0^T \alpha_0(\mathbf{X}_i)} \\ & \left. \left. \left. \times \beta_0^T [\mathbf{Z}_i - E\{\mathbf{Z}_i | \beta_0^T \alpha_0(\mathbf{X}_i)\}] \Theta_\gamma^T \right\}^{-1} \right) \right\|_2 = O_p(h_b^{-1}) \end{aligned} \tag{S55}$$

by (S28). In addition,

$$\|\mathbf{M}\|_2 \leq \sqrt{N} \|\mathbf{M}\|_\infty.$$

Now since J is of finite dimension, the order of $\|\mathbf{M}\|_\infty$ is the same as the order of each element in \mathbf{M} . Further

$$\mathbf{M} = E \left[\int_0^1 \{B_{rk}(t), k = 2, \dots, d_\gamma\}^T \mathbf{C}_{14i}(t) dt \right]$$

with

$$\begin{aligned} \mathbf{C}_{14i}(t) = & [\mathbf{X}_i(t) - E\{\mathbf{X}_i(t) | \beta_0^T \alpha_0(\mathbf{X}_i)\}]^T \beta_0 \alpha_0(\mathbf{X}_i)^T \partial[g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} \\ & - E\{g^*\{Y_i, \beta_0^T \alpha_0(\mathbf{X}_i)\} | \beta_0^T \alpha_0(\mathbf{X}_i)\}] / \partial\{\beta_0^T \alpha_0(\mathbf{X}_i)\}. \end{aligned}$$

Each (k, l) th element of \mathbf{M} , M_{kl} , can be written as

$$M_{kl} = E \left[\int_0^1 \{B_{rk}(t)\} C_{14li}(t) dt \right],$$

where $C_{14li}(t)$ is the l th element of $C_{14i}(t)$. Since $E\{C_{14li}(t)\} \neq 0$, $|E\{C_{14li}(t)\}| < \infty$ and $\|C_{14li}(\cdot)\|_2 < \infty$. By (S50), we have $|M_{kl}| = O_p(h_b)$, $\|\mathbf{M}\|_\infty = O_p(h_b)$ and in turn

$$\|\mathbf{M}\|_2 \leq \sqrt{N} O_p(h_b) = O_p(h_b^{1/2}). \quad (\text{S56})$$

Hence $\|\widehat{\boldsymbol{\gamma}}^-(\boldsymbol{\beta})/\partial\boldsymbol{\beta}^\top|_{\boldsymbol{\beta}=\boldsymbol{\beta}^*}\|_2 = O_p(\|\mathbf{P}\|_2) = O_p(h_b^{-1/2})$. This proves the result. \square

S5 Correlation coefficients between the four air pollutants CO, NO₂, O₃ and SO₂

$$\begin{array}{c} \text{CO} \\ \text{NO}_2 \\ \text{O}_3 \\ \text{SO}_2 \end{array} \begin{pmatrix} \text{CO} & \text{NO}_2 & \text{O}_3 & \text{SO}_2 \\ 1.00 & 0.69 & -0.32 & 0.35 \\ 0.69 & 1.00 & -0.15 & 0.38 \\ -0.32 & -0.15 & 1.00 & -0.16 \\ 0.35 & 0.38 & -0.16 & 1.00 \end{pmatrix}$$

S6 Figures

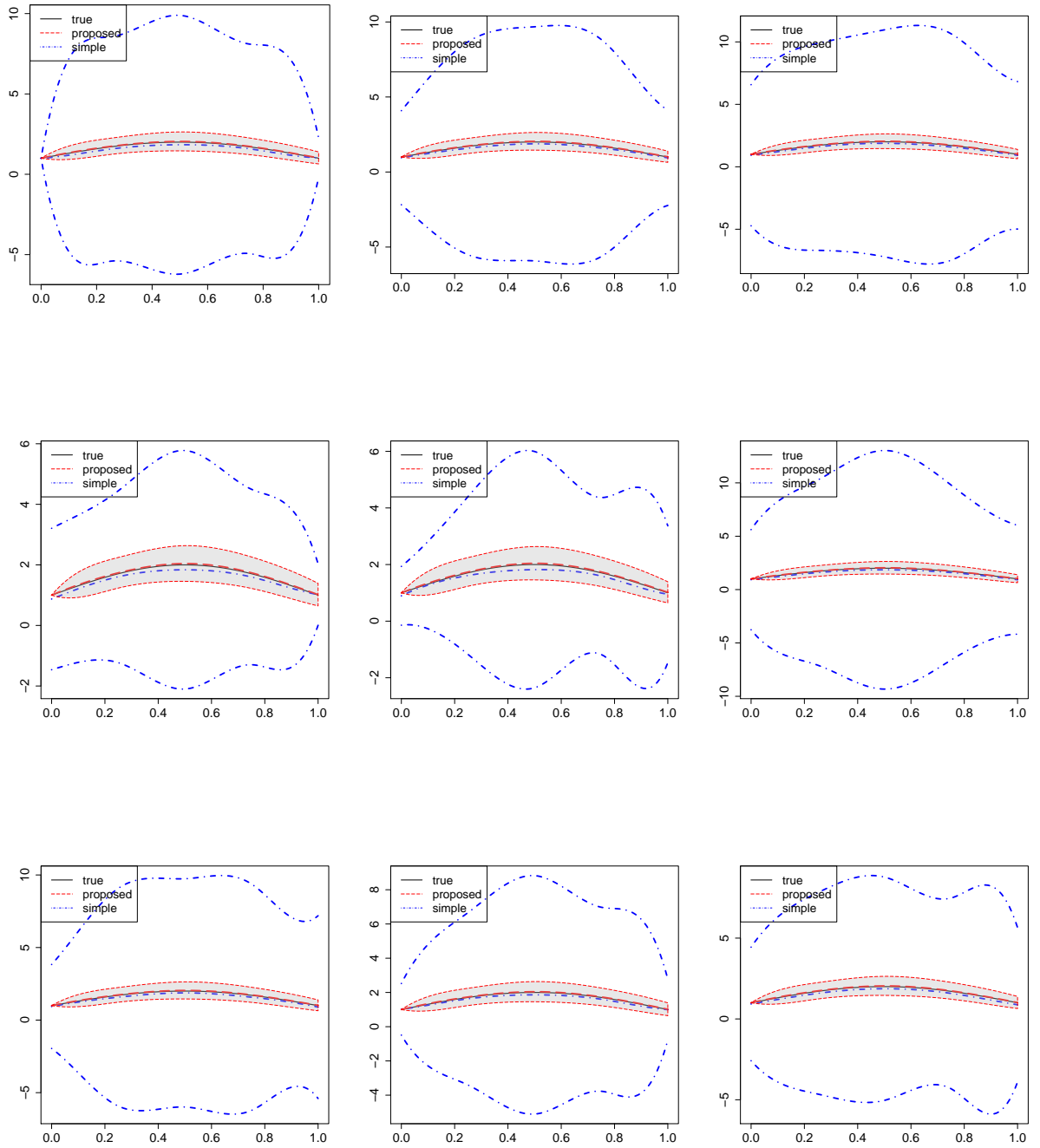


Figure S1: Simulation 2: Comparison of estimators of $\beta_k \alpha(t)$ based on (1) and $\beta_k(t)$ based on the model $f_{Y|\mathbf{X}(t)}\{Y, \mathbf{X}(t)\} = f\{Y, \int_0^1 \boldsymbol{\beta}(t)^\top \mathbf{X}(t) dt\}$ for $k = 1, \dots, 9$.

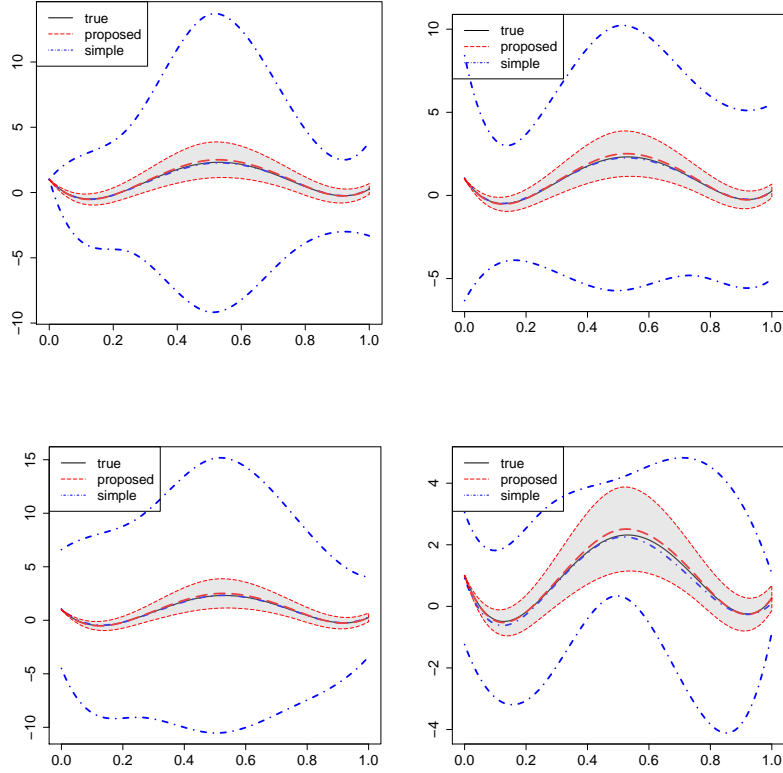


Figure S2: Simulation 3: Comparison of estimators of $\beta_k \alpha(t)$ based on (1) and $\beta_k(t)$ based on the model $f_{Y|\mathbf{X}(t)}\{Y, \mathbf{X}(t)\} = f\{Y, \int_0^1 \boldsymbol{\beta}(t)^\top \mathbf{X}(t) dt\}$ for $k = 1, \dots, 4$.

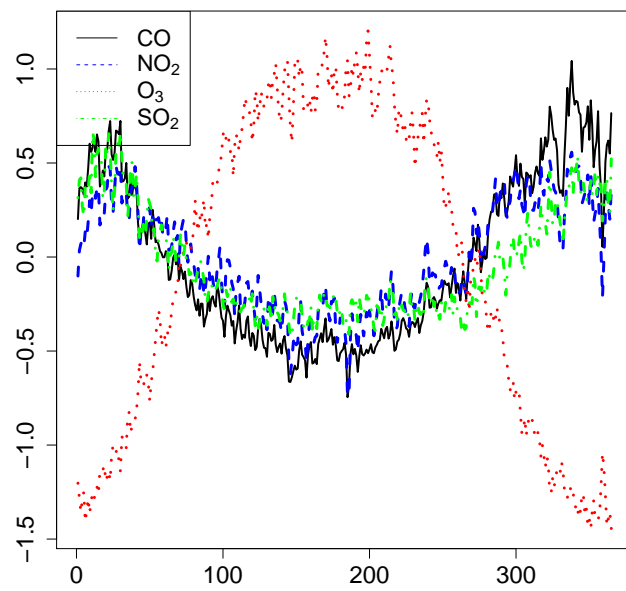


Figure S3: The point-wise mean trajectories of four air pollutants.

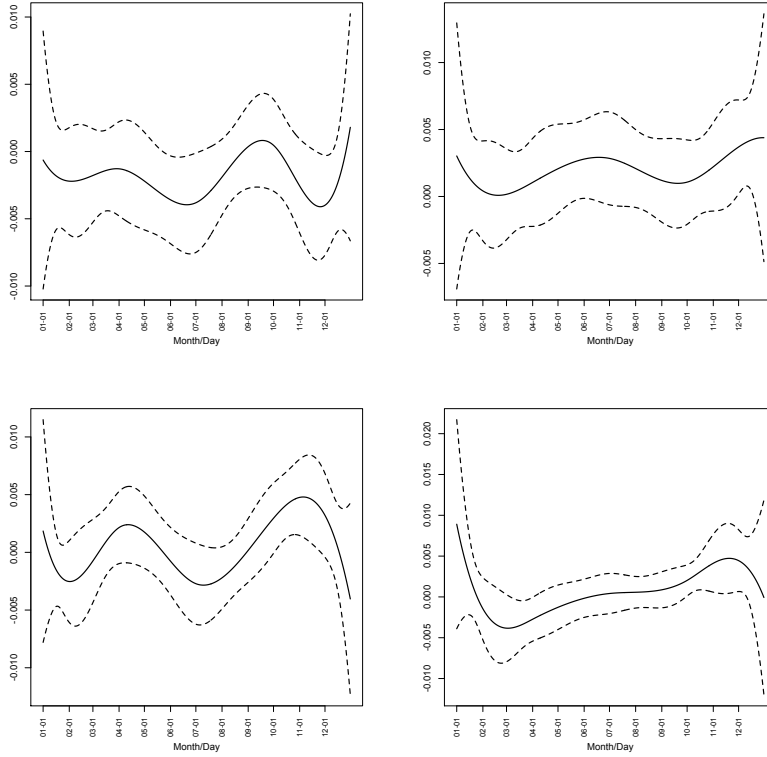


Figure S4: The estimated functional coefficient $\hat{\eta}(t)$ when fitting the functional linear model $E(Y) = \int_0^1 \eta(t)X(t)dt$ in the air pollution data, where the response variable Y is the annual CVD death rate, and the functional covariate $X(t)$ is the daily concentration of the air pollutant CO (the top left panel), NO_2 (the top right panel), SO_2 (the bottom left panel), and O_3 (the bottom right panel). The dashed lines are the pointwise 95% confidence intervals for $\eta(t)$.

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