

## ONLINE APPENDIX

### A Comparison with Horowitz (1998)

It is possible to study Horowitz's (1998) smoothed QR estimator using the same tools we employ to document the asymptotic behavior of our convolution-type kernel QR estimator. Let  $\tau \in (0, 1)$  and Assumptions X, Q and K hold. Let now  $\mathfrak{R}_h^{(j)}(b; \tau) := \mathbb{E}[\widehat{\mathfrak{R}}_h^{(j)}(b; \tau)]$  for  $j = 0, 1, 2$  and  $\mathbf{b}_h(\tau) := \arg \min_b \mathfrak{R}_h(b; \tau)$ . The latter corresponds to the unique solution of the first-order condition  $\mathfrak{R}_h^{(1)}(\mathbf{b}_h(\tau); \tau) = 0$  for  $h$  small enough. It turns out that  $\widehat{\mathfrak{R}}_h^{(2)}(b; \tau) = \frac{1}{n} \sum_{i=1}^n X_i X_i' \kappa(e_i(b)/h)$ , where  $\kappa(t) := 2k(t) + tk^{(1)}(t)$ . Integrating by parts shows that  $\int t^j tk^{(1)}(t) dt = -(j+1) \int t^j k(t) dt$ , so that  $\kappa(\cdot)$  is a kernel function with the same order than  $k(\cdot)$ . Accordingly, Horowitz's (1998) smoothed objective function also satisfies Lemma 1.

Along the same lines as in the proof of Theorem 1,

$$\begin{aligned} \mathbf{b}_h(\tau) - \beta_h(\tau) &= - \left[ \mathfrak{R}^{(2)}(\beta(\tau); \tau) + o(1) \right]^{-1} \mathfrak{R}_h^{(1)}(\beta_h(\tau); \tau) \\ &= [D^{-1}(\tau) + o(1)] \mathbb{E} \left[ X \frac{e(\beta_h(\tau))}{h} k \left( -\frac{e(\beta_h(\tau))}{h} \right) \right]. \end{aligned}$$

Because  $k(\cdot)$  is symmetric and of order  $s+1$ , Theorem 1 implies that

$$\begin{aligned} \mathbb{E} \left[ X \frac{e(\beta_h(\tau))}{h} k \left( -\frac{e(\beta_h(\tau))}{h} \right) \right] &= h \mathbb{E} \left[ X \int zk(z) f(X'\beta_h(\tau) + hz | X) k(z) dz \right] \\ &= h^{s+1} \frac{\int z^{s+1} k(z) dz}{s!} \mathbb{E} [X f^{(s)}(X'\beta(\tau) | X)] + o(h^{s+1}) \end{aligned}$$

and that  $\mathbf{b}_h(\tau) = \beta_h(\tau) + (s+1)h^{s+1}B(\tau) + o(h^{s+1}) = \beta(\tau) + sh^{s+1}B(\tau) + o(h^{s+1})$ . This means that  $\mathbf{b}_h(\tau) - \beta(\tau) = -s(\beta_h(\tau) - \beta(\tau)) + o(h^{s+1})$ , so that Horowitz's (1998) smoothing approach amplifies the bias by a factor  $-s$  asymptotically.

We next consider the asymptotic covariance matrix of Horowitz's smoothed QR estimator. Consider  $b_h(\tau) = \beta(\tau) + O(h^2)$  and let  $\Delta_h(\tau) := \widehat{\mathfrak{R}}_h^{(1)}(b_h(\tau); \tau) - \widehat{R}_h^{(1)}(b_h(\tau); \tau)$ . We first observe that  $\mathbb{V}[\sqrt{n}\Delta_h(\tau)] = O(h)$ , whereas using the fact  $y = X'b_h(\tau) - hu$  yields under Assumption Q2 that

$$\begin{aligned} n \text{Cov}(\widehat{R}_h^{(1)}(b_h(\tau); \tau), \Delta_h(\tau)) &= \mathbb{E} \left\{ XX' \int \left[ \tau - K \left( -\frac{e(b_h(\tau))}{h} \right) \right] \frac{e(b_h(\tau))}{h} k \left( -\frac{e(b_h(\tau))}{h} \right) f(y|X) dy \right\} \\ &= h \int [K(u) - \tau] uk(u) du \mathbb{E} [XX' f(X'b_h(\tau)|X) dy] + O(h^2) \\ &= h \int_0^\infty [K(u) - K(-u)] uk(u) du \mathbb{E} [XX' f(X'\beta(\tau)|X) dy] + O(h^2) \end{aligned}$$

for any symmetric kernel  $k(\cdot)$ . Because  $\int_0^\infty [K(u) - K(-u)] uk(u) du > 0$  for second-order and *bona fide* higher-order kernels, there exists a symmetric positive  $M_\tau$  such that

$$\mathbb{V} \left[ \sqrt{n} \widehat{\mathfrak{R}}_h^{(1)}(\beta(\tau); \tau) \right] = \mathbb{V} \left[ \sqrt{n} \widehat{R}_h^{(1)}(\beta(\tau); \tau) \right] + h[M_\tau + o(1)].$$

It then follows from Lemma 1 that  $\mathfrak{R}_h^{(2)}(\mathbf{b}_h(\tau); \tau) = D(\tau) + o(1)$ , and hence

$$\mathbb{V}\left[\mathfrak{R}_h^{(2)}(\mathbf{b}_h(\tau); \tau)^{-1} \widehat{\mathfrak{R}}_h^{(1)}(\mathbf{b}_h(\tau); \tau)\right] = \mathbb{V}\left[R_h^{(2)}(\beta_h(\tau); \tau)^{-1} \widehat{R}_h^{(1)}(\beta_h(\tau); \tau)\right] + h D^{-1}(\tau) M_\tau D^{-1}(\tau) + o(h).$$

Horowitz's estimator has a Bahadur-Kiefer representation as in Theorem 2, ergo the above equality shows that the asymptotic covariance matrix of Horowitz's estimator is larger than ours at the second order.

## B Technical proofs

**Proof of Lemma 1** Under Assumption Q2, a Taylor expansion with integral remainder yields

$$f(v + hz | x) = \sum_{\ell=0}^s f^{(\ell)}(v | x) \frac{(hz)^\ell}{\ell!} + \frac{(hz)^s}{(s-1)!} \int_0^1 (1-w)^{s-1} \left[ f^{(s)}(v + whz | x) - f^{(s)}(v | x) \right] dw.$$

(i) Assumption K1 ensures that

$$\begin{aligned} \mathbb{E}[k_h(v - Y) | x] - f(v | x) &= \int k_h(v - y) f(y | x) dy - f(v | x) \\ &= \int k(z) \left[ f(v + hz | x) - f(v | x) \right] dz \\ &= \int_0^1 (1-w)^{s-1} \int \frac{(hz)^s}{(s-1)!} k(z) \left[ f^{(s)}(v + whz | x) - f^{(s)}(v | x) \right] dz dw \quad (23) \end{aligned}$$

through a change of variables  $y = v + hz$ . Now, the check function is such that

$$\int \rho_\tau(v) dG(v) = (1 - \tau) \int_{-\infty}^0 G(v) dv + \tau \int_0^\infty [1 - G(v)] dv$$

for any arbitrary cdf  $G$ , and hence

$$R(b; \tau) = \int \left\{ (1 - \tau) \int_{-\infty}^0 \int_{-\infty}^{t+x'b} f(v | x) dv dt + \tau \int_0^\infty \int_{t+x'b}^\infty f(v | x) dv dt \right\} dF_X(x),$$

where  $F_X(x)$  is the cdf of  $X$ . Similarly,

$$R_h(b; \tau) = \int \left\{ (1 - \tau) \int_{-\infty}^0 \int_{-\infty}^{t+x'b} \mathbb{E}[k_h(v - Y) | x] dv dt + \tau \int_0^\infty \int_{t+x'b}^\infty \mathbb{E}[k_h(v - Y) | x] dv dt \right\} dF_X(x).$$

It follows from (23) that

$$\begin{aligned} L_1 &:= \left| \int_{-\infty}^0 \int_{-\infty}^{t+x'b} \left\{ \mathbb{E}[k_h(v - Y) | x] - f(v | x) \right\} dv dt \right| \\ &= \left| \int_0^1 (1-w)^{s-1} \int \frac{(hz)^s}{(s-1)!} k(z) \int_{-\infty}^0 \int_{-\infty}^{t+x'b} \left[ f^{(s)}(v + whz | x) - f^{(s)}(v | x) \right] dv dt dz dw \right| \\ &= \left| \int_0^1 (1-w)^{s-1} \int \frac{(hz)^s}{(s-1)!} k(z) \left[ f^{(s-2)}(x'b + whz | x) - f^{(s-2)}(x'b | x) \right] dz dw \right| \end{aligned}$$

given that  $\int |z^{s+1} k(z)| dz < \infty$  by Assumption K1 and that  $f^{(s-2)}(\cdot | \cdot)$  is Lipschitz. Analogously,  $\left| \int_0^\infty \int_{t+x'b}^\infty \mathbb{E}[k_h(v - Y) | x] - f(v | x) dv dt \right| \leq C h^{s+1}$ , establishing the result.

(ii) By the definitions of  $R(b; \tau)$  and  $R_h(b; \tau)$ , it follows from the Lebesgue dominated convergence theorem that

$$R^{(1)}(b; \tau) = \mathbb{E} \left[ X \left( F(X'b | X) - \tau \right) \right] = \int x \left[ \int_{-\infty}^{x'b} f(y | x) dy - \tau \right] dF_X(x),$$

and that

$$R_h^{(1)}(b; \tau) = \mathbb{E} \left\{ X \left[ K \left( \frac{X'b - Y}{h} \right) - \tau \right] \right\} = \int x \left\{ \int_{-\infty}^{x'b} \mathbb{E}[k_h(v - Y) | x] dv - \tau \right\} dF_X(x). \quad (24)$$

In view that  $\int z^s k(z) dz = 0$  and  $\int |z^{s+1} k(z)| dz < \infty$ , integrating (23) yields

$$\begin{aligned} L_2 &:= \left| \int_{-\infty}^{x'b} \mathbb{E}[k_h(v - Y) | x] - f(v | x) dv \right| \\ &= \left| \int_0^1 (1-w)^{s-1} \int \frac{(hz)^s}{(s-1)!} k(z) \int_{-\infty}^{x'b} \left[ f^{(s)}(v + whz | x) - f^{(s)}(v | x) \right] dv dz dw \right| \\ &= \left| \int_0^1 (1-w)^{s-1} \int \frac{(hz)^s}{(s-1)!} k(z) \left[ f^{(s-1)}(x'b + whz | x) - f^{(s-1)}(x'b | x) \right] dz dw \right| \\ &= \left| \int_0^1 w(1-w)^{s-1} \int \frac{(hz)^{s+1}}{(s-1)!} k(z) \int_0^1 f^{(s)}(x'b + twhz | x) dt dz dw \right| \leq C h^{s+1}, \end{aligned} \quad (25)$$

uniformly given that  $f^{(s)}$  is bounded. The result then readily follows from Assumption X.

(iii) Differentiating  $R^{(1)}(b; \tau)$  with respect to  $b$  results in

$$R^{(2)}(b; \tau) = \mathbb{E}[X X' f(X'b | X)] = \int x x' f(x'b | x) dF_X(x)$$

and, likewise,

$$R_h^{(2)}(b; \tau) = \mathbb{E}[X X' k_h(X'b - Y)] = \int x x' \mathbb{E}[k_h(x'b - Y) | x] dF_X(x).$$

Setting  $v = x'b$  in (23) then yields

$$\begin{aligned} \left\| R_h^{(2)}(b; \tau) - R^{(2)}(b; \tau) \right\| &\leq C \left| \mathbb{E}[k_h(v - Y) | x] - f(v | x) \right| \\ &\leq C h^s \int |z^s K(z)| \sup_{(x,y) \in \mathbb{R}^{d+1}} \sup_{t: |t| \leq hz} \left| f^{(s)}(y + t | x) - f^{(s)}(y | x) \right| dz = o(h^s), \end{aligned}$$

under Assumptions X and Q2 by the Lebesgue dominated convergence theorem, as stated.

(iv) Recall that

$$R_h^{(2)}(b; \tau) = \mathbb{E}[X X' k_h(X'b - Y)] = \int k(z) \int x x' f(x'b + hz | x) dF_X(x) dz.$$

Under Assumption Q2, it ensues from  $f(\cdot | \cdot)$  being Lipschitz that

$$\left\| R_h^{(2)}(b + \delta; \tau) - R_h^{(2)}(b; \tau) \right\| \leq C \int |k(z)| \int \|x x'\| |x' \delta| dF_X(x) dz \leq C \|\delta\|,$$

uniformly in  $(b, h, \delta, \tau)$ , completing the proof. ■

**Proof of Lemma 3** For  $\eta > 0$ ,

$$\begin{aligned}
\left\{ \sup_{(\tau, h)} \left\| \widehat{\beta}_h(\tau) - \beta_h(\tau) \right\| \geq 2\eta \right\} &= \bigcup_{(\tau, h)} \left\{ \left\| \widehat{\beta}_h(\tau) - \beta_h(\tau) \right\| \geq 2\eta \right\} \\
&\subset \bigcup_{(\tau, h)} \left\{ \inf_{\{b: \|b - \beta_h(\tau)\| \geq 2\eta\}} \widehat{\mathcal{R}}_h(b; \tau) \leq \inf_{\{b: \|b - \beta_h(\tau)\| \leq 2\eta\}} \widehat{\mathcal{R}}_h(b; \tau) \right\} \\
&\subset \bigcup_{(\tau, h)} \left\{ \inf_{\{b: \|b - \beta_h(\tau)\| \geq 2\eta\}} \widehat{\mathcal{R}}_h(b; \tau) \leq \widehat{\mathcal{R}}_h(\beta_h(\tau); \tau) \right\} \\
&= \bigcup_{(\tau, h)} \left\{ \inf_{\{b: \|b - \beta_h(\tau)\| \geq 2\eta\}} \widehat{\mathcal{R}}_h(b; \tau) \leq 0 \right\},
\end{aligned}$$

given that  $\widehat{\mathcal{R}}_h(\beta_h(\tau); \tau) = 0$ . Theorem 1 ensures that

$$\begin{aligned}
\left\{ b : \|b - \beta_h(\tau)\| \geq 2\eta \right\} &\subset \left\{ b : \|b - \beta(\tau)\| + \sup_{(\tau, h)} \|\beta_h(\tau) - \beta(\tau)\| \geq 2\eta \right\} \\
&\subset \left\{ b : \|b - \beta(\tau)\| + O(\bar{h}_n^{s+1}) \geq 2\eta \right\} \\
&\subset \left\{ b : \|b - \beta(\tau)\| \geq \eta \right\}
\end{aligned}$$

for all  $(\tau, h)$  provided that  $n$  is large enough. This means that

$$\left\{ \sup_{(\tau, h)} \left\| \widehat{\beta}_h(\tau) - \beta_h(\tau) \right\| \geq 2\eta \right\} \subset \bigcup_{(\tau, h)} \left\{ \inf_{\{b: \|b - \beta(\tau)\| \geq \eta\}} \widehat{\mathcal{R}}_h(b; \tau) \leq 0 \right\}.$$

As  $t \mapsto \rho_\tau(t)$  is 1-Lipschitz, it follows from

$$\widehat{R}_h(b; \tau) = \frac{1}{nh} \sum_{i=1}^n \int \rho_\tau(t) k\left(\frac{t - (Y_i - X_i' b)}{h}\right) dt = \frac{1}{n} \sum_{i=1}^n \int \rho_\tau(Y_i - X_i' b + hz) k(z) dz$$

that

$$\left| \widehat{R}_h(b; \tau) - \widehat{R}(b; \tau) \right| = \left| \frac{1}{n} \sum_{i=1}^n \int \left[ \rho_\tau(Y_i - X_i' b + hz) - \rho_\tau(Y_i - X_i' b) \right] k(z) dz \right| \leq h \int |z k(z)| dz < \infty,$$

for all  $b, \tau$  and  $h$  by Assumption K1. Theorem 1 and the Lipschitz property of  $b \mapsto \widehat{R}(b; \tau)$  then ensures that  $\widehat{\mathcal{R}}_h(b; \tau) \geq \widehat{\mathcal{R}}(b; \tau) - C h$  uniformly in  $b$  and  $\tau$ , so that

$$\left\{ \sup_{(\tau, h)} \left\| \widehat{\beta}_h(\tau) - \beta_h(\tau) \right\| \geq 2\eta \right\} \subset \bigcup_{(\tau, h)} \left\{ \inf_{\{b: \|b - \beta(\tau)\| \geq \eta\}} \widehat{\mathcal{R}}(b; \tau) \leq C h \right\}.$$

The next step is a convexity argument. We first perform the change of variables  $b = \beta(\tau) + \rho u$  with  $\|u\| = 1$  and  $\rho \geq \eta$ . In view that  $b \mapsto \widehat{\mathcal{R}}(b; \tau)$  is convex with  $\widehat{\mathcal{R}}(\beta(\tau); \tau) = 0$ ,

$$\frac{\eta}{\rho} \widehat{\mathcal{R}}(\beta(\tau) + \rho u; \tau) = \frac{\eta}{\rho} \widehat{\mathcal{R}}(\beta(\tau) + \rho u; \tau) + \left(1 - \frac{\eta}{\rho}\right) \widehat{\mathcal{R}}(\beta(\tau); \tau) \geq \widehat{\mathcal{R}}(\beta(\tau) + \eta u; \tau).$$

It follows from the above inequality that

$$\left\{ \inf_{\{b: \|b - \beta(\tau)\| \geq \eta\}} \widehat{\mathcal{R}}(b; \tau) \leq C h \right\} \subset \left\{ \inf_{\{b: \|b - \beta(\tau)\| = \eta\}} \widehat{\mathcal{R}}(b; \tau) \leq C h \right\},$$

and hence

$$\begin{aligned} \bigcup_{(\tau, h)} \left\{ \left\| \widehat{\beta}_h(\tau) - \beta_h(\tau) \right\| \geq 2\eta \right\} &\subset \bigcup_{\tau} \left\{ \inf_{\{b: \|b - \beta(\tau)\| = \eta\}} \widehat{\mathcal{R}}(b; \tau) \leq C \bar{h}_n \right\} \\ &\subset \left\{ \inf_{\tau} \inf_{\{b: \|b - \beta(\tau)\| = \eta\}} \left[ \widehat{\mathcal{R}}(b; \tau) - \mathcal{R}(b; \tau) \right] \leq C \bar{h}_n - \inf_{\tau} \inf_{\{b: \|b - \beta(\tau)\| = \eta\}} \mathcal{R}(b; \tau) \right\}. \end{aligned}$$

We next establish an upper bound for  $C \bar{h}_n - \inf_{\tau \in [\underline{\tau}, \bar{\tau}]} \inf_{\{b: \|b - \beta(\tau)\| = \eta\}} \mathcal{R}(b; \tau)$  using the fact that the eigenvalues of  $\mathcal{R}^{(2)}(b; \tau)$  are bounded away from 0 uniformly in  $b$ , for  $\|b - \beta(\tau)\| \leq 1$  and  $\tau \in [\underline{\tau}, \bar{\tau}]$ . Given that  $R^{(1)}(\beta(\tau), \tau) = 0$ , a second-order Taylor expansion of  $\mathcal{R}(b; \tau) = R(b; \tau) - R(\beta(\tau); \tau)$  gives way to

$$\mathcal{R}(b; \tau) = 0 + (b - \beta(\tau))' \left[ \int_0^1 (1-t) \mathcal{R}^{(2)}(\beta(\tau) + t[b - \beta(\tau)]; \tau) dt \right] (b - \beta(\tau)) \geq C \eta^2$$

for all  $b$  such that  $\|b - \beta(\tau)\| = \eta$ . This means that, for any  $\eta_2 = \eta - \epsilon_2 < \eta$  with conformable  $\epsilon_2$  and  $\bar{h}_n$  small enough,

$$\bigcup_{(\tau, h)} \left\{ \left\| \widehat{\beta}_h(\tau) - \beta_h(\tau) \right\| \geq 2\eta \right\} \subset \left\{ \sup_{\tau \in [\underline{\tau}, \bar{\tau}]} \sup_{\{b: \|b - \beta(\tau)\| = \eta\}} \left| \widehat{\mathcal{R}}(b; \tau) - \mathcal{R}(b; \tau) \right| \geq C \eta_2^2 \right\}.$$

Now, let  $Z_i = (Y_i, X_i')'$ ,  $\theta = (\tau, b')'$  and  $g_1(Z_i, \theta) = \rho_{\tau}(Y_i - X_i' b) - \rho_{\tau}(Y_i - X_i' \beta(\tau))$ , so that

$$\widehat{\mathcal{R}}(b; \tau) - \mathcal{R}(b; \tau) = \frac{1}{n} \sum_{i=1}^n \{g_1(Z_i, \theta) - \mathbb{E}[g_1(Z_i, \theta)]\}.$$

Under Assumption X, it follows from  $\eta \leq 1$  that, for all  $b$  such that  $\|b - \beta(\tau)\| = \eta$  and  $\tau \in [\underline{\tau}, \bar{\tau}]$ ,

$$|g_1(Z_i, \theta)| \leq \|X_i\| \|b - \beta(\tau)\| \leq C,$$

implying that  $\mathbb{V}(g_1(Z_i, \theta)) \leq \sigma^2 \leq C$ . Observe also that pairing Assumption X with the Lipschitz conditions on  $\tau \mapsto \beta(\tau)$  in Assumption Q1 and on  $\tau \mapsto \rho_{\tau}(u)$  entails, for all admissible  $z$ ,

$$|g_1(z, \theta_1) - g_1(z, \theta_2)| \leq C \|\theta_1 - \theta_2\|, \quad (26)$$

where  $\|\theta\|^2 = \|b\|^2 + |\tau|^2$ . Next, for  $\delta > 0$ , let  $\theta_j$ , with  $j = 1, \dots, J(\delta) \leq C \delta^{-(d+1)}$ , be such that

$$\Theta = \left\{ \theta = (b, \tau) : \tau \in [\underline{\tau}, \bar{\tau}], \|b - \beta(\tau)\| = \eta_1 \right\} \subset \bigcup_{j=1}^{J(\delta)} \mathcal{B}(\theta_j, \delta),$$

where  $\mathcal{B}(\theta_j, \delta)$  is the  $\|\cdot\|$ -ball with center  $\theta_j$  and radius  $\delta$ . Define  $\underline{g}_{1j}(\cdot)$  and  $\bar{g}_{1j}(\cdot)$  respectively as  $\underline{g}_{1j}(z) := \inf_{\theta \in \mathcal{B}(\theta_j, \delta)} g_1(z, \theta)$  and  $\bar{g}_{1j}(z) = \sup_{\theta \in \mathcal{B}(\theta_j, \delta)} g_1(z, \theta)$ , so that  $\{g_1(\cdot, \theta) : \theta \in \mathcal{B}(\theta_j, \delta)\} \subset [\underline{g}_{1j}, \bar{g}_{1j}]$ . Let  $\mathcal{G}_{1, \Theta} := \{g_1(\cdot, \theta) : \theta \in \Theta\} \subset \bigcup_{j=1}^{J(\delta)} [\underline{g}_{1j}, \bar{g}_{1j}]$ . It follows from (26) that  $|\bar{g}_{1j}(z) - \underline{g}_{1j}(z)| \leq C \delta \leq C$  and  $\mathbb{E} \left[ |\bar{g}_{1j}(Z_i) - \underline{g}_{1j}(Z_i)|^2 \right] \leq C \delta^2$ . By conditions (i) and (ii) in Lemma 2, it follows from (18) that setting  $H(\delta) = -(d+1) \ln \delta + C$  leads to

$$\Pr \left( \sup_{\theta \in \Theta} \left| \widehat{\mathcal{R}}(b; \tau) - \mathcal{R}(b; \tau) \right| \geq C \frac{1 + \sqrt{r} + r/\sqrt{n}}{\sqrt{n}} \right) \leq \exp(-r).$$

This means that, for  $n$  large enough with respect to  $\eta_2^2$ ,

$$\Pr \left( \sup_{\tau} \sup_{\{b: \|b - \beta(\tau)\| = \eta_1\}} \left| \widehat{\mathcal{R}}(b; \tau) - \mathcal{R}(b; \tau) \right| \geq C\eta_2^2 \right) \leq C \exp(-n C\eta_2^4),$$

and hence

$$\Pr \left( \sup_{(\tau, h)} \left\| \widehat{\beta}_h(\tau) - \beta_h(\tau) \right\| \geq 2\eta \right) \leq C \exp(-n C\eta_2^4),$$

completing the proof. ■

**Proof of Lemma 4** We start with the first deviation probability. As  $R_h^{(1)}(\beta_h(\tau), \tau) = 0$ ,

$$\sup_{(\tau, h)} \left\| \sqrt{n} \widehat{R}_h^{(1)}[\beta_h(\tau), \tau] \right\| \leq \sup_{(\tau, h)} \sup_{\{b: \|b - \beta_h(\tau)\| \leq \eta\}} \left\| \sqrt{n} \left( \widehat{R}_h^{(1)}(b, \tau) - R_h^{(1)}(b, \tau) \right) \right\|.$$

However,

$$\widehat{R}_h^{(1)}(b, \tau) = \frac{\partial}{\partial b} \left[ \frac{1}{n} \sum_{i=1}^n \int \rho_{\tau}(Y_i - X_i' b + h z) k(z) dz \right] = \frac{1}{n} \sum_{i=1}^n X_i \left[ \int \mathbb{I}(Y_i - X_i' b + h z < 0) k(z) dz - \tau \right],$$

implying that  $\widehat{R}_h^{(1)}(b, \tau) = \sum_{i=1}^n g_2(Z_i, \theta)/n$ , with

$$g_2(Z_i, \theta) = X_i \left[ \int \mathbb{I}(Y_i - X_i' b + h z < 0) k(z) dz - \tau \right],$$

for  $Z_i = (Y_i, X_i')'$  and  $\theta \in \Theta := \{(b', h, \tau) : (\tau, h) \in [\underline{\tau}, \bar{\tau}] \times [\underline{h}_n, \bar{h}_n], \|b - \beta_h(\tau)\| \leq \eta\}$ . We bound each of the entries of  $\widehat{R}_h^{(1)}(b, \tau)$ , so that there is no loss of generality in assuming that  $X_i$  is univariate. Note that  $|g_2(Z_i, \theta)| \leq C$ ,  $\mathbb{V}(g_2(Z_i, \theta)) \leq \sigma^2 \leq C$ , and  $|g_2(Z_i, \theta_2) - g_2(Z_i, \theta_1)| \leq C$  for all  $\theta_1$  and  $\theta_2$ . Let  $\|\theta\|^2 = \|b\|^2 + |h|^2 + |\tau|^2$  and let  $\mathcal{B}(\theta, \delta^2)$  denote the  $\|\cdot\|$ -ball with center  $\theta$  and radius  $\delta^2$ . Assumption X ensures that, for any  $\theta_1$  and  $\theta_2$  in  $\mathcal{B}(\theta, \delta^2)$ ,

$$|g_2(Z_i, \theta_2) - g_2(Z_i, \theta_1)| \leq C \left[ \int \mathbb{I}(Y_i - X_i' b + h z \in [-C\delta^2, C\delta^2]) |k(z)| dz + \delta^2 \right]. \quad (27)$$

Consider a covering of  $\Theta$  with  $J(\delta^2) \leq C \delta^{-2(d+1)}$  balls  $\mathcal{B}(\theta_j, \delta^2)$ . Letting  $\underline{g}_{2j}(z) := \inf_{\theta \in \mathcal{B}(\theta_j, \delta)} g_2(z, \theta)$  and  $\bar{g}_{2j}(z) = \sup_{\theta \in \mathcal{B}(\theta_j, \delta)} g_2(z, \theta)$  implies not only that  $\{g_2(\cdot, \theta) : \theta \in \mathcal{B}(\theta_j, \delta)\} \subset [\underline{g}_{2j}, \bar{g}_{2j}]$ , but also that  $\mathcal{G}_{2, \Theta} := \{g_2(\cdot, \theta) : \theta \in \Theta\} \subset \bigcup_{j=1}^{J(\delta^2)} [\underline{g}_{2j}, \bar{g}_{2j}]$ . Equation (27) ensures that, uniformly in  $j$  and  $\delta^2 \leq \sigma^2$ ,

$$\mathbb{E} \left[ |\bar{g}_{2j}(Z_i) - \underline{g}_{2j}(Z_i)|^2 \right] \leq C \delta^4 + C \mathbb{E} \left[ \int \mathbb{I}(Y_i - X_i' b + h z \in [-C\delta^2, C\delta^2]) |k(z)| dz \right]^2.$$

Applying the Cauchy-Schwarz inequality under Assumptions K and Q2 then gives way to

$$\begin{aligned} L_4 &:= \mathbb{E} \left[ \int \mathbb{I}(Y_i - X_i' b - h z \in [-C\delta^2, C\delta^2]) k(z) dz \right]^2 \\ &\leq \mathbb{E} \left[ \int \mathbb{I}(Y_i - X_i' b - h z \in [-C\delta^2, C\delta^2]) |k(z)| dz \right] \times \int |k(z)| dz \\ &\leq \int \mathbb{E} \{ \Pr(Y_i - X_i b - h z \in [-C\delta^2, C\delta^2] | X_i) \} |k(z)| dz \times \int |k(z)| dz \\ &\leq C \delta^2, \end{aligned}$$

implying that  $\mathbb{E} \left[ |\bar{g}_{2j}(Z_i) - g_{2j}(Z_i)|^2 \right] \leq C(\delta^4 + \delta^2) \leq C\delta^2$ , uniformly in  $j$  and  $\delta^2 \leq \sigma^2$ . As a result, conditions (i) and (ii) in Lemma 2 hold for  $\ln H(\delta) = -2(d+1)\ln \delta + C$ , so that (18) gives

$$\Pr \left( \sup_{\theta \in \Theta} \left\| \sqrt{n} \left( \hat{R}_h^{(1)}(b, \tau) - R_h^{(1)}(b, \tau) \right) \right\| \geq C(\sqrt{r} + 1 + r/\sqrt{n}) \right) \leq 2\exp(-r).$$

Accordingly, the first bound holds for  $n$  large enough. As for the second bound, there is no loss of generality to assume that  $X_i$  is unidimensional. Note that  $\sqrt{nh/\ln n} \hat{R}_h^{(2)}(b, \tau) = \sum_{i=1}^n g_3(Z_i, \theta)/\sqrt{n}$ , with

$$g_3(Z_i, \theta) := \sqrt{\frac{1}{h \ln n}} X_i^2 k \left( \frac{X_i' b - Y_i}{h} \right).$$

Assumptions K and X ensure that, uniformly for  $\theta \in \Theta$ ,

$$|g_3(Z_i, \theta)| \leq C \sqrt{\frac{1}{h \ln n}} \leq C \frac{O(\sqrt{n})}{\ln^2 n}.$$

It also follows from Assumption Q2 that, uniformly for  $\theta \in \Theta$ ,

$$\begin{aligned} \mathbb{V}(g_3(Z_i, \theta)) &\leq \frac{C}{h \ln n} \int \int k \left( \frac{x'b - y}{h} \right) f(y|x) dy dF_X(x) \\ &= \frac{C}{\ln n} \times \int \int k(v) f(x'b + hv|x) dv dF_X(x) \leq \frac{C}{\ln n} = \sigma_n^2. \end{aligned}$$

Assumption K posits that, for any  $\theta_1$  and  $\theta_2$  in  $\Theta$ ,  $|g_3(Z_i, \theta_1) - g_3(Z_i, \theta_2)| \leq C n^C \|\theta_1 - \theta_2\|$ . Consider a covering of  $\Theta$  with  $J(\delta/n^C) \leq C(\delta/n^C)^{-(d+1)}$  balls  $\mathcal{B}(\theta_j, \delta/n^C)$  and let  $\underline{g}_{3j}(z) := \inf_{\theta \in \mathcal{B}(\theta_j, \delta)} g_3(z, \theta)$  and  $\bar{g}_{3j}(z) := \sup_{\theta \in \mathcal{B}(\theta_j, \delta)} g_3(z, \theta)$ . It then turns out that  $\{g_3(z, \theta) : \theta \in \mathcal{B}(\theta_j, \delta)\} \subset [\underline{g}_{3j}, \bar{g}_{3j}]$  and hence  $\mathcal{G}_{3, \Theta} = \{g_3(\cdot, \theta) : \theta \in \Theta\} \subset \bigcup_{j=1}^{J(\delta/n^C)} [\underline{g}_{3j}, \bar{g}_{3j}]$ , with  $\mathbb{E} \left[ |\bar{g}_3(Z_i) - \underline{g}_3(Z_i)|^2 \right] \leq C\delta^2$ . Conditions (i) and (ii) in Lemma 2 thus hold for  $\ln H(\delta) = -2(d+1)(\ln \delta - C \ln n) + C$ , so that (18) results for any  $u > 0$  in

$$\Pr \left( \sup_{\theta \in \Theta} \left\| \sqrt{\frac{nh}{\ln n}} \left( \hat{R}_h^{(2)}(b, \tau) - R_h^{(2)}(b, \tau) \right) \right\| \geq C \left( 1 + \frac{\sqrt{u}}{\sqrt{\ln n}} + \frac{u}{\ln n} \right) \right) \leq 2\exp(-u).$$

Setting  $u = r \ln n$  then yields the exponential inequality.

Suppose now, without loss of generality, that  $\mathcal{B}$  is convex. Recall that

$$\hat{R}_h^{(2)}(b_1, \tau) - \hat{R}_h^{(2)}(b_0, \tau) = \frac{1}{n} \sum_{i=1}^n X_i X_i' X_i (b_1 - b_0) \int_0^1 \frac{1}{h^2} k^{(1)} \left( \frac{Y_i X_i' [b_1 + t(b_1 - b_0)]}{h} \right) dt$$

and that the variance of  $h^{-2} k^{(1)}((Y_i - X_i' b)/h)$  is of order  $h^{-3} = o(n/\ln n)$  under Assumption K. Applying now the same arguments as in the proof of the exponential inequality yields

$$\begin{aligned} &\frac{1}{n} \sum_{i=1}^n X_i X_i' X_i (b_1 - b_0) \frac{1}{h^2} k^{(1)} \left( \frac{Y_i - X_i' [b_1 + t(b_1 - b_0)]}{h} \right) \\ &= \mathbb{E} \left[ X X' X (b_1 - b_0) \int_{-\infty}^{\infty} \frac{1}{h} k \left( \frac{y - X[b_1 + t(b_1 - b_0)]}{h} \right) f^{(1)}(y|X) dy \right] + O_p \left( \sqrt{\frac{\ln n}{nh^3}} \right), \end{aligned}$$

uniformly in  $(\tau, h, b_0, b_1)$  for  $t \in [0, 1]$ . The proofs of the remaining results follow similarly.  $\blacksquare$

**Proof of Proposition 3** Let

$$\mathcal{E}_n^3(\epsilon) := \left\{ \sup_{(\tau, h)} \left\| \hat{\beta}_h(\tau) - \beta_h(\tau) \right\| \geq \epsilon^{1/4} \right\},$$

which is such that  $\Pr(\mathcal{E}_n^3(\epsilon)) \leq C \exp(-C n \epsilon)$  by Lemma 3. The bounds for  $\Pr(\mathcal{E}_n^1(r))$  and  $\Pr(\mathcal{E}_n^2(r))$  follow from Lemma 4. In particular,  $\lim_{n \rightarrow \infty} \Pr(\mathcal{E}_n^2(r)) = 0$ , whereas Lemma 1 ensures under Assumption X that  $b \mapsto \hat{R}_h(b; \tau)$  is strictly convex for  $b$  in a vicinity of  $\beta_h(\tau)$ , for all  $\tau$  in  $[\underline{\tau}, \bar{\tau}]$  with probability at least  $1 - \Pr(\mathcal{E}_n^1(r)) - \Pr(\mathcal{E}_n^2(r))$ . But, by Lemma 3 and Theorem 1, all minimizers of  $\hat{R}_h(b; \tau)$  lie in such a vicinity with a probability tending to 1. This means that we can make  $1 - \Pr(\mathcal{E}_n^1(r)) - \Pr(\mathcal{E}_n^2(r))$  arbitrarily close to 1 by increasing  $r$ , and hence  $\hat{\beta}_h(\tau)$  is unique with a probability going to 1 as  $n$  increases. It also follows that, in case  $\check{\mathcal{E}}_n^1(r)$ ,  $\check{\mathcal{E}}_n^2(r)$  and  $\check{\mathcal{E}}_n^3(\epsilon)$  are all true and  $n$  is large enough,  $\hat{\beta}_h(\tau)$  satisfies the first-order condition  $\hat{R}_h^{(1)}(\hat{\beta}_h(\tau); \tau) = 0$ . Recall from the proof of Theorem 1 that  $\hat{R}_h^{(2)}(\cdot; \tau)$  has an inverse in the vicinity of  $\beta_h(\tau)$  for  $n$  large enough on  $\mathcal{E}^2(r)$ . Applying the implicit function theorem then yields  $\hat{\beta}_h(\tau)$  continuous over the admissible  $(\tau, h)$ . Accordingly,

$$\begin{aligned} -\hat{R}_h^{(1)}(\beta_h(\tau); \tau) &= \hat{R}_h^{(1)}(\hat{\beta}_h(\tau); \tau) - \hat{R}_h^{(1)}(\beta_h(\tau); \tau) \\ &= [\hat{\beta}_h(\tau) - \beta_h(\tau)] \int_0^1 \hat{R}_h^{(2)}\left(\beta_h(\tau) + t[\hat{\beta}_h(\tau) - \beta_h(\tau)]; \tau\right) dt. \end{aligned}$$

Now, if  $\epsilon$  in  $\mathcal{E}_n^3(\epsilon)$  is small enough, the eigenvalues of the above matrix are in  $[1/C, C]$  for a large  $C$  provided that  $n$  is large enough, uniformly in  $\tau$  and  $h$ . This means that

$$\hat{\beta}_h(\tau) - \beta_h(\tau) = - \left[ \int_0^1 \hat{R}_h^{(2)}\left(\beta_h(\tau) + u[\hat{\beta}_h(\tau) - \beta_h(\tau)]; \tau\right) du \right]^{-1} \hat{R}_h^{(1)}(\beta_h(\tau); \tau). \quad (28)$$

Lemma 1(iv) then implies that, for a generic constant  $C$  coming from Bernstein-type inequalities,

$$\begin{aligned} P_2 &:= \left\| \sqrt{n}(\hat{\beta}_h(\tau) - \beta_h(\tau)) + [R_h^{(2)}(\beta_h(\tau); \tau)]^{-1} \sqrt{n} \hat{R}_h^{(1)}(\beta_h(\tau); \tau) \right\| \\ &\leq C \left\| \int_0^1 \left[ \hat{R}_h^{(2)}\left(\beta_h(\tau) + u[\hat{\beta}_h(\tau) - \beta_h(\tau)]; \tau\right) - R_h^{(2)}\left(\beta_h(\tau) + u[\hat{\beta}_h(\tau) - \beta_h(\tau)]; \tau\right) \right] du \right\| \left\| \sqrt{n} \hat{R}_h^{(1)}(\beta_h(\tau); \tau) \right\| \\ &\quad + C \left\| \int_0^1 \left[ R_h^{(2)}\left(\beta_h(\tau) + u[\hat{\beta}_h(\tau) - \beta_h(\tau)]; \tau\right) - R_h^{(2)}(\beta_h(\tau); \tau) \right] du \right\| \left\| \sqrt{n} \hat{R}_h^{(1)}(\beta_h(\tau); \tau) \right\| \\ &\leq C \left\{ \sqrt{\frac{\ln n}{nh}} r^2 + \left\| \hat{\beta}_h(\tau) - \beta_h(\tau) \right\| \left\| \sqrt{n} \hat{R}_h^{(1)}(\beta_h(\tau); \tau) \right\| \right\} \\ &\leq C \left\{ \sqrt{\frac{\ln n}{nh}} r^2 + n^{-1/2} \left\| \sqrt{n} \hat{R}_h^{(1)}(\beta_h(\tau); \tau) \right\|^2 \right\} \\ &\leq C \left( \sqrt{\frac{\ln n}{nh}} + \frac{1}{\sqrt{n}} \right) r^2 \end{aligned}$$

on  $\check{\mathcal{E}}_n^1(r)$  and  $\check{\mathcal{E}}_n^2(r)$ , implying that  $\check{\mathcal{E}}_n(r)$  holds as long as  $C_0$  of the Proposition is large enough.  $\blacksquare$

**Proof of Lemma 5** Let  $h = h_n$  to simplify notation. We first note that  $\mathbb{E}(\sqrt{n} \hat{S}_h(\tau)) = 0$ . In addition, for any  $\alpha, \tau \in [\underline{\tau}, \bar{\tau}]$ , it follows that

$$\mathbb{V}(\sqrt{n} \hat{S}_h(\tau), \sqrt{n} \hat{S}_h(\varsigma)) = \mathbb{E} \left\{ X X' \left[ K \left( -\frac{e(\beta_h(\tau))}{h} \right) - \tau \right] \left[ K \left( -\frac{e(\beta_h(\varsigma))}{h} \right) - \varsigma \right] \right\}$$



converges to  $\mathbb{E}\{XX'(\mathbb{I}[X'\beta(\tau) \geq Y] - \tau)(\mathbb{I}[X'\beta(\varsigma) \geq Y] - \varsigma)\}$  as  $n \rightarrow \infty$ . A simple computation using iterated expectations then yields the limiting covariance structure in (22).

By the Cramér-Wold device, in order to obtain weak convergence for the  $d$ -dimensional process  $\{\sqrt{n}\widehat{S}_h : \tau \in [\underline{\tau}, \bar{\tau}]\}$ , it suffices to consider the convergence in distribution of the linear form  $\{\sqrt{n}\lambda'\widehat{S}_h : \tau \in [\underline{\tau}, \bar{\tau}]\}$ , where  $\lambda$  is an arbitrary (fixed) vector in  $\mathbb{R}^d$ . Assume without loss of generality that  $\|X\| \leq 1$  and  $\|\lambda\| \leq 1$ , and let  $Z = (Y, X) \in \mathbb{R} \times \mathbb{R}^d$  and, similarly,  $Z_i = (Y_i, X_i)$ . Define now  $g_{n,\tau} : \mathbb{R} \times \text{supp}X \rightarrow \mathbb{R}$  for  $z = (y, x)$  as

$$g_{n,\tau}(z) := x_\lambda \left\{ K \left( \frac{x'\beta_h(\tau) - y}{h} \right) - \tau \right\}, \quad (29)$$

where  $x_\lambda = \lambda'x$  and  $X_\lambda = \lambda'X$ , and consider the class of functions  $\mathcal{G}_n = \{g_{n,\tau} : \tau \in [\underline{\tau}, \bar{\tau}]\}$ . Letting  $\mathbb{P}$  and  $\mathbb{P}_n$  respectively denote the distribution of  $Z$  and the empirical distribution of the sample  $(Z_1, \dots, Z_n)$  yields

$$\sqrt{n}\lambda'\widehat{S}_h(\tau) = \sqrt{n}(\mathbb{P}_n g_{n,\tau} - \mathbb{P} g_{n,\tau}).$$

In other words, the process  $\{\sqrt{n}\lambda'\widehat{S}_h : \tau \in [\underline{\tau}, \bar{\tau}]\}$  is an empirical process indexed by a (changing) class of functions  $\mathcal{G}_n$ . By Theorem 19.28 in van der Vaart (1998), it suffices to establish that

$$\sup_{|\tau - \varsigma| < \delta(n)} \mathbb{E}|g_{n,\tau}(Z) - g_{n,\varsigma}(Z)|^2 \rightarrow 0 \quad (30)$$

and that, for any  $\delta(n) \downarrow 0$ ,

$$\int_0^{\delta(n)} \sqrt{\ln N_{[]}(\epsilon, \mathcal{G}_n, L^2(\mathbb{P}))} d\epsilon \rightarrow 0 \quad (31)$$

with  $N_{[]}(\epsilon, \mathcal{G}_n, L^2(\mathbb{P}))$  denoting the minimum number of  $\epsilon$ -brackets in  $L^2(\mathbb{P})$  required to cover  $\mathcal{G}_n$ . The remaining requirements of Theorem 19.28 indeed hold trivially in view that the index set  $[\underline{\tau}, \bar{\tau}]$  is a compact—and so, totally bounded—metric space, and that the changing classes  $\mathcal{G}_n$  admit envelope functions  $G_n \equiv 1$  for all  $n$  that satisfy the Lindeberg condition  $\mathbb{E}_{\mathbb{P}}(G_n^2 \mathbb{I}[G_n > \sqrt{n}\epsilon]) \rightarrow 0$ .

Let  $\partial_\tau := \frac{\partial}{\partial \tau}$ . By Lemma 1 and Theorem 1, applying twice the implicit function theorem yields

$$\partial_\tau \beta_h(\tau) = -D_h(\tau)^{-1} \partial_\tau R_h^{(1)}(\beta_h(\tau); \tau) = D_h(\tau)^{-1} \mathbb{E}(X) = [D(\tau) + o(1)]^{-1} \mathbb{E}(X) = \partial_\tau \beta(\tau) + o(1)$$

uniformly for  $(\tau, h) \in [\underline{\tau}, \bar{\tau}] \times [\underline{h}, \bar{h}]$ . This implies, by Assumption Q1, that  $\sup \|\partial_\tau \beta_h(\tau)\| \leq C$  for  $n$  large enough, with supremum taken over  $(\tau, h) \in [\underline{\tau}, \bar{\tau}] \times [\underline{h}_n, \bar{h}_n]$ , and so  $\|\beta_h(\tau) - \beta_h(\varsigma)\| \leq C|\tau - \varsigma|$ . It also follows from the inverse function theorem and Assumption Q1 that  $\tau \mapsto x'\beta_h(\tau)$  is strictly increasing in  $\tau$ , for any  $x \in \text{supp}X$  and  $n$  large enough. In what follows, we assume that  $n$  is large enough, so that the above holds.

Now, let  $\underline{\tau} \leq \tau_L \leq \tau_U \leq \bar{\tau}$  and consider two random elements (possibly degenerate)  $\widehat{\tau}$  and  $\widehat{\varsigma}$  in  $[\tau_L, \tau_U]$ . The mean value theorem and Assumption Q2 then ensure that

$$\Pr \left( x'\beta_h(\widehat{\tau} \wedge \widehat{\varsigma}) - hu \leq Y \leq x'\beta_h(\widehat{\tau} \vee \widehat{\varsigma}) - hu \mid X = x \right) \leq C|\tau_U - \tau_L|, \quad (32)$$

uniformly for  $u \in \mathbb{R}$  and  $x \in \text{supp}X$ , given that  $[x'\beta_h(\widehat{\tau} \wedge \widehat{\varsigma}), x'\beta_h(\widehat{\tau} \vee \widehat{\varsigma})] \subset [x'\beta_h(\tau_L), x'\beta_h(\tau_U)]$  and  $|x'\beta_h(\tau_U) - x'\beta_h(\tau_L)| \leq C|\tau_U - \tau_L|$ . Define  $\Upsilon_u = \{X'\beta_h(\widehat{\tau} \wedge \widehat{\varsigma}) - Y \leq hu \leq X'\beta_h(\widehat{\tau} \vee \widehat{\varsigma}) - Y\}$ .

It follows from  $|g_{n,\hat{\tau}}(Z) - g_{n,\hat{\varsigma}}(Z)| \leq \int \mathbb{I}(\Upsilon_u) |k(u)| du + |\hat{\tau} - \hat{\varsigma}|$  that

$$\begin{aligned} \mathbb{E}|g_{n,\hat{\tau}}(Z) - g_{n,\hat{\varsigma}}(Z)|^2 &\leq \mathbb{E}|\hat{\tau} - \hat{\varsigma}|^2 + 2\mathbb{E}\left[|\hat{\tau} - \hat{\varsigma}| \int \mathbb{I}(\Upsilon_u) |k(u)| du\right] + \mathbb{E}\left[\int \mathbb{I}(\Upsilon_u) |k(u)| du\right]^2 \\ &\leq |\tau_U - \tau_L|^2 + 2|\tau_U - \tau_L| \int \Pr(\Upsilon_u) |k(u)| du + C \int \Pr(\Upsilon_u) |k(u)| du \quad (33) \\ &\leq C|\tau_U - \tau_L|, \quad (34) \end{aligned}$$

given that the Cauchy-Schwarz inequality implies that  $\int \mathbb{I}(\Upsilon_u) |k(u)| du \int |k(u)| du$  is an upper bound for  $\left(\int \mathbb{I}(\Upsilon_u) |k(u)|^{1/2} |k(u)|^{1/2} du\right)^2$ ,  $\int |k(u)| du < \infty$  by Assumption K1, and  $\Pr(\Upsilon_u) = \mathbb{E}[\Pr(\Upsilon_u | X)] \leq C|\tau_U - \tau_L|$  by iterated expectations and (32). Taking  $\hat{\tau}$  and  $\hat{\varsigma}$  to be deterministic shows that (30) holds, for all  $\delta(n) \downarrow 0$ .

We now obtain a set of brackets whose bracketing number is of order  $1/\epsilon$ . For  $\epsilon > 0$  small enough, we cover the interval  $[\underline{\tau}, \bar{\tau}]$  with  $J(\epsilon) \leq \lceil (\bar{\tau} - \underline{\tau})/\epsilon + 1 \rceil \leq 2/\epsilon$  open intervals  $B_i = (\tau_i - \epsilon, \tau_i + \epsilon)$ , and let  $\bar{g}_n^i(z) = \sup_{\tau \in B_i} g_{n,\tau}(z)$  and  $\underline{g}_n^i(z) = \inf_{\tau \in B_i} g_{n,\tau}(z)$ . It is straightforward to appreciate that the collection formed by the brackets  $[\underline{g}_n^i, \bar{g}_n^i]$ , with  $i = 1, \dots, J(\epsilon)$ , covers  $\mathcal{G}_n$  and that these suprema and infima are attained in the closure of  $B_i$ .<sup>6</sup> In particular,  $\bar{g}_n^i(Z) = g_{n,\hat{\tau}_i}(Z)$  and  $\underline{g}_n^i(Z) = g_{n,\hat{\varsigma}_i}(Z)$ , where  $\hat{\tau}_i$  and  $\hat{\varsigma}_i$  are random elements in  $[\tau_i - \epsilon, \tau_i + \epsilon]$ . Resorting to (34) once more then gives

$$\mathbb{E}|\bar{g}_n^i(Z) - \underline{g}_n^i(Z)|^2 \leq C\epsilon,$$

and, as a result,  $N_{[]}(\epsilon, \mathcal{G}_n, L^2(P)) \leq C/\epsilon$ . This ensures that (31) holds for all  $\delta(n) \downarrow 0$ . ■

---

<sup>6</sup> For  $i = 1$  and  $i = J(\epsilon)$ , the intervals are actually  $[\underline{\tau}, \tau_1 + \epsilon]$  and  $[\tau_{J(\epsilon)} - \epsilon, \bar{\tau}]$ , respectively. For simplicity of exposition, we keep the notation as above.