



where  $\varepsilon$  is a random variable with mean zero and finite variance.

Let  $(X_1, Y_1), \dots, (X_n, Y_n)$  be a random sample.

$$(1) \quad Y = g(X) + \varepsilon,$$

where  $X$  is a random variable with density  $L_2(\mathcal{I})$  on the interval  $\mathcal{I} = [0, 1]$ ,  $g$  is a measurable function in  $L_2(\mathcal{I})$  and  $\varepsilon$  is a random variable independent of  $X$ , with mean zero and finite variance. The regression function  $g$  is assumed to be linear, i.e.,  $g(x) = a + bx$ , where  $a$  and  $b$  are unknown parameters. The asymptotic variance of the maximum likelihood estimator of  $a$  and  $b$  is  $n^{-1/2}$ , where  $n$  is the sample size; see Hamed (1991), Hamed (2002), Hamed (2003), Hamed (2003), Hamed (2005), Hamed (2005), and Hamed (2007).

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Let  $\psi_1, \psi_2, \dots, \psi_\infty$  be a complete orthonormal system in  $L_2(\mathcal{I})$ , where  $\mathcal{I} = [0, 1]$ . The covariance function  $V(s, t) = \text{Cov}\{X(s), X(t)\}$ :

$$(2) \quad V(s, t) = \sum_{j=1}^{\infty} \theta_j \psi_j(u) \psi_j(v),$$

where  $\psi_j$  is a complete orthonormal system in  $L_2(\mathcal{I})$ , and  $\theta_j$  is a sequence of non-negative numbers. The covariance function  $V$  is assumed to be positive definite; see Hamed (2007).

$\theta_1 \geq \theta_2 \geq \dots$ . For  $m, r \in \mathbb{N}$ , let  $\psi_j, \dots, \theta_j, \dots$  be a sequence of functions  $V, V$ ,

$$(3) \quad V(s, t) = \frac{1}{n} \sum_{i=1}^n \{X_i(s) - \bar{X}(s)\} \{X_i(t) - \bar{X}(t)\} = \sum_{j=1}^{\infty} \hat{\theta}_j \hat{\psi}_j(s) \hat{\psi}_j(t),$$

where  $\bar{X} = n^{-1} \sum_{i=1}^n X_i$  is the sample mean,  $\hat{\theta}_1 \geq \hat{\theta}_2 \geq \dots$  is a sequence of positive numbers,  $\hat{\psi}_j, \dots, \theta_j, \dots$  is a sequence of functions  $\hat{\psi}_{n+1}, \hat{\psi}_{n+2}, \dots$  is a sequence of functions

$$(4) \quad X - E(X) = \sum_{j=1}^{\infty} \xi_j \psi_j,$$

where  $\xi_j = \int X \psi_j$  is the coefficient of  $\psi_j$  in the expansion of  $X - E(X)$  in terms of  $\psi_j$ . For  $j \geq n+1$ , let  $\hat{\psi}_{n+1}, \hat{\psi}_{n+2}, \dots$  be a sequence of functions

such that  $\hat{\psi}_j = \psi_j$  for  $j \leq n$  and  $\hat{\psi}_j = 0$  for  $j > n$ . In [2], we have shown that the sequence  $\hat{\psi}_j$  is a sequence of functions. In [3], we have shown that the sequence  $\hat{\psi}_j$  is a sequence of functions. In [4], we have shown that the sequence  $\hat{\psi}_j$  is a sequence of functions. In [5], we have shown that the sequence  $\hat{\psi}_j$  is a sequence of functions.

## 2. Preliminary and notations

$$\hat{g}(x) = \frac{\sum_{i=1}^n Y_i K_i(x)}{\sum_{i=1}^n K_i(x)},$$

where  $K_i(x) = K(\|x - X_i\|/h)$ ,  $K$  is a kernel function,  $h$  is a bandwidth,  $\|\cdot\|$  is the norm in  $L^2$  norm. In [2006], we have shown that the sequence  $\hat{g}(x)$  is a sequence of functions. In [1], we have shown that the sequence  $\hat{g}(x)$  is a sequence of functions. In [2], we have shown that the sequence  $\hat{g}(x)$  is a sequence of functions. In [3], we have shown that the sequence  $\hat{g}(x)$  is a sequence of functions. In [4], we have shown that the sequence  $\hat{g}(x)$  is a sequence of functions. In [5], we have shown that the sequence  $\hat{g}(x)$  is a sequence of functions.

... m ... r ... m ... r ... m ... r ... m ... r ... m ... r ... (7).

... m ... r ... m ... r ... m ... r ... m ... r ... m ... r ... (8).

A  $\mathcal{M}$  1. ... r ... K ... [0, c], ... c > 0, ... r ... K ... [0, c].

... r ... g ... x ... r ... r g\_x ... r ... r ... y ... r ... r \delta,

$$g(x + \delta y) = g(x) + \delta g_x y + o(\delta)$$

... \delta \rightarrow 0. ... m ... r ...

$$(5) \quad g_x = \sum_{j=1}^{\infty} \gamma_{xj} t_j,$$

... \gamma\_{xj} = g\_x \psi\_j ... r ... t\_j ... r ... y\_j = t\_j(y) = y \psi\_j. ... \gamma\_{xj} ... m ... g\_x ... \psi\_j.

... m ... r ... r g\_x, ... r ... m ... \gamma\_{xj}, ... r ... m ... a\_x^m = (a\_{x1}^m, a\_{x2}^m, \dots) ... a\_x^m = (a\_{x1}^m, a\_{x2}^m, \dots) ... r ... a = (a\_1, a\_2, \dots) ... m ... m ... m ... |g\_x a|, ...

$$g_x a = \sum_{j=1}^{\infty} \gamma_{xj} a_j$$

where  $\hat{\psi}_j$  is the kernel estimator of  $\psi_j$  based on  $\mathcal{X}_n$  and  $\mathcal{Y}_n$ .

$$(7) \quad \hat{\gamma}_{xj} = \frac{\sum_{i_1, i_2}^{(j)} Y_{i_1 i_2} K(i_1, i_2, j|x)}{\sum_{i_1, i_2}^{(j)} \hat{\xi}_{i_1 i_2 j} K(i_1, i_2, j|x)}.$$

where  $\sum_{i_1, i_2}^{(j)} = \sum_{i_1, i_2: \hat{\xi}_{i_1 i_2 j} > 0}$ .

$$(8) \quad K(i_1, i_2, j|x) = K \left( \frac{\|x - X_{i_1}\|}{h_1} \right) K \left( \frac{\|x - X_{i_2}\|}{h_1} \right) K \left( \frac{Q_{i_1 i_2 j}}{h_2} \right),$$

where  $K(\cdot) = \frac{1}{h_1} \mathbb{1}_{\|\cdot\| \leq h_1}$  and  $Q_{i_1 i_2 j} = \frac{1}{h_2} \mathbb{1}_{\|X_{i_1} - X_{i_2}\| \leq h_2} \hat{\psi}_j(X_{i_1}, X_{i_2}, x)$ .

### 3. The eca e e e

3.1. Consistency and convergence rates of estimators of  $g$ . Let  $\mathcal{X} = \{x \in \mathcal{I} : \delta(x) > 0\}$ .

Assumption 2.

$$(9) \quad \lim_{\|y\| \leq 1} |g(x + \delta y) - g(x)| \rightarrow 0 \quad \text{as } \delta \downarrow 0,$$

where  $h = h(n) \rightarrow 0$  as  $n \rightarrow \infty$  and  $nP(\|X - x\| \leq c_1 h) \rightarrow \infty$  as  $n \rightarrow \infty$ .

$$(10) \quad h = h(n) \rightarrow 0 \quad \text{as } n \rightarrow \infty, \quad nP(\|X - x\| \leq c_1 h) \rightarrow \infty \quad \text{as } n \rightarrow \infty,$$

where  $c_1 = c$ ,  $K(c) > 0$ , and  $c_1 \in (0, c)$ .

Let  $C > 0$ ,  $x \in L_2(\mathcal{I})$ , and  $\alpha \in (0, 1]$ . Let  $\mathcal{G}(C, x, \alpha)$  be the set of functions  $g$  such that  $|g(x + \delta y) - g(x)| \leq C\delta^\alpha$ , for all  $y \in L_2(\mathcal{I})$  with  $\|y\| \leq 1$ , and  $0 \leq \delta \leq 1$ .

Theorem 1. If Assumptions 1 and 2 hold, then  $\hat{g}(x) \rightarrow g(x)$  in mean square, conditional on  $\mathcal{X}$ , and

$$(11) \quad E[\{\hat{g}(x) - g(x)\}^2 | \mathcal{X}] = o_p(1).$$

$g \in \mathcal{G}(C, x, \alpha)$

Furthermore, for all  $\eta > 0$ ,

$$P_{g \in \mathcal{G}(\hat{C}, x, \alpha)}\{|\hat{g}(x) - g(x)| > \eta\} \rightarrow 0.$$

Moreover, if  $h$  is chosen to decrease to zero in such a manner that

$$(12) \quad h^{2\alpha} P(\|X - x\| \leq c_1 h) \asymp n^{-1}$$

as  $n \rightarrow \infty$ , then, for each  $C > 0$ , the rate of convergence of  $\hat{g}(x)$  to  $g(x)$  equals  $O_p(h^{2\alpha})$ , uniformly in  $g \in \mathcal{G}(C, x, \alpha)$ :

$$(13) \quad E_{g \in \mathcal{G}(\hat{C}, x, \alpha)}[\{\hat{g}(x) - g(x)\}^2 | \mathcal{X}] = O_p(h^{2\alpha}),$$

$$(14) \quad \lim_{C_1 \rightarrow \infty} \lim_{n \rightarrow \infty} \sup_{g \in \mathcal{G}(\hat{C}, x, \alpha)} P\{|\hat{g}(x) - g(x)| > C_1 h^\alpha\} = 0.$$

From (11)–(13), we can see that  $\hat{g}(x) = \hat{g}(X_i, \varepsilon_i)$ ,  $1 \leq i < \infty$ , where  $\hat{g}(X_i, \varepsilon_i) = \hat{g}(X_i, Y_i) = g(X_i) + \varepsilon_i$ . Let  $Y_i = Y_i(g) = g(X_i) + \varepsilon_i$ . Then  $\hat{g}(X_i, Y_i) = \hat{g}(X_i, Y_i(g))$ . In Section 5.1, we will show that (12) and (13) hold. A more detailed proof can be found in (2007). From (14), we can see that

2. If the error  $\varepsilon$  in (1) is normally distributed, and if, for a constant  $c_1 > 0$ ,  $nP(\|X - x\| \leq c_1 h) \rightarrow \infty$  and (12) holds, then, for any estimator  $\tilde{g}(x)$  of  $g(x)$ , and for  $C > 0$  sufficiently large in the definition of  $\mathcal{G}(C, x, \alpha)$ , there exists a constant  $C_1 > 0$ , such that

$$\lim_{n \rightarrow \infty} \sup_{g \in \mathcal{G}(\hat{C}, x, \alpha)} P\{|\tilde{g}(x) - g(x)| > C_1 h^\alpha\} > 0.$$

As a result, we can see that  $\tilde{g}(x)$  is not a uniformly efficient estimator of  $g(x)$  in  $\mathcal{G}(C, x, \alpha)$ . In Section 5.1, we will show that (12) holds. In Section 5.1, we will show that (12) holds.

3.2. Consistency of derivative estimator. In this section, we will consider the consistency of the derivative estimator  $\hat{\gamma}_{xj}$ .

$$q_{12j} = 1 - \frac{|(X_1 - X_2)\psi_j|^2}{\|X_1 - X_2\|^2}$$

where  $Q_{12j} = \hat{\xi}_{1i_2} \hat{\xi}_j - \hat{\xi}_{1i_2} \hat{\xi}_j$ ,  $k_{i_1 i_2 j} = K(i_1, i_2, j | x)$ , and  $Q_{i_1 i_2 j} = q_{i_1 i_2 j}$ . (8)

Assumption 3.

- (1)  $\sup_{t \in \mathcal{I}} E\{X(t)^4\} < \infty$ ;
- (2)  $\theta_1, \dots, \theta_{j+1}$ ;
- (3)  $|g(x+y) - g(x) - g_x y| = o(\|y\|)$  as  $\|y\| \rightarrow 0$ ;
- (4)  $\xi_{1j} - \xi_{2j}$ ;
- (5)  $K \in [0, 1]$ ,  $0 < K(0) < \infty$ ;
- (6)  $h_1, h_2 \rightarrow 0$ ,  $n h_1^2 E(k_{i_1 i_2 j}) \rightarrow \infty$ .

Let  $X_j = X(t_j)$ ,  $\psi_j = \psi(t_j)$ ,  $\hat{\psi}_j = \hat{\psi}(t_j)$ . By Assumption 3,  $\|\hat{\psi}_j - \psi_j\| = o_p(n^{-1/2})$ .

Let  $X = X(t)$ ,  $\psi = \psi(t)$ ,  $\hat{\psi} = \hat{\psi}(t)$ . By Assumption 3,  $\|\hat{\psi} - \psi\| = o_p(n^{-1/2})$ . Let  $\theta_j = \theta(t_j)$ ,  $L_j = L(t_j)$ . By Assumption 3,  $n^{-\varepsilon} = O(h_j)$  for  $j = 1, 2$  and  $\varepsilon > 0$ . Let  $C_1 > 0$ . By Assumption 3,  $nh_1 P(\|x - X\| \leq h_1) \rightarrow \infty$  and  $nh_1^{C_1+1} \rightarrow \infty$  for  $C_1 > 0$ . Let  $C_2 > 0$ . By Assumption 3,  $nh_2 P(q_{12j} \leq h_2) = O(h_2^{C_1})$  for  $C_1 > 0$ . By Assumption 3,  $nh_2 P(q_{12j} \leq C_2 h_2) \rightarrow \infty$  for  $C_2 > 0$ .

Theorem 3. If Assumption 3 holds, then  $\hat{\gamma}_{xj} \rightarrow \gamma_{xj}$  in probability.

Proof. By (5),  $e = \sum_{j=1}^{j_0} e_j \psi_j$ ,  $\sum_{j=1}^{j_0} e_j^2 = 1$ ,  $j_0 < \infty$ . By (6),  $e = \sum_{j=1}^{j_0} e_j \gamma_{xj}$ . Let  $a_j = e_j$ ,  $1 \leq j \leq j_0$ ,  $a_j = 0$ ,  $j > j_0$ . By Assumption 3,  $\hat{g}_x e = \sum_{j=1}^{j_0} e_j \hat{\gamma}_{xj}$ . By Assumption 3,  $\hat{g}_x e \rightarrow g_x e$ . Let  $\hat{g}_x a = \sum_{j=1}^{j_0} \hat{\gamma}_{xj} a_j$ . By Assumption 3,  $\hat{g}_x a \rightarrow g_x a = \sum_{j=1}^{j_0} a_j \psi_j$ .

$g_x a = \sum_j \gamma_{xj} a_j$ ,  $\sum_j \gamma_{xj}^2 < \infty$ ,  $r = r(n, x) \rightarrow \infty$  as  $n \rightarrow \infty$ ;  $\|a\| < \infty$ ,  $\hat{g}_x a - g_x a \rightarrow 0$  as  $n \rightarrow \infty$ .

**4. A characterization of a eeg a g da.**

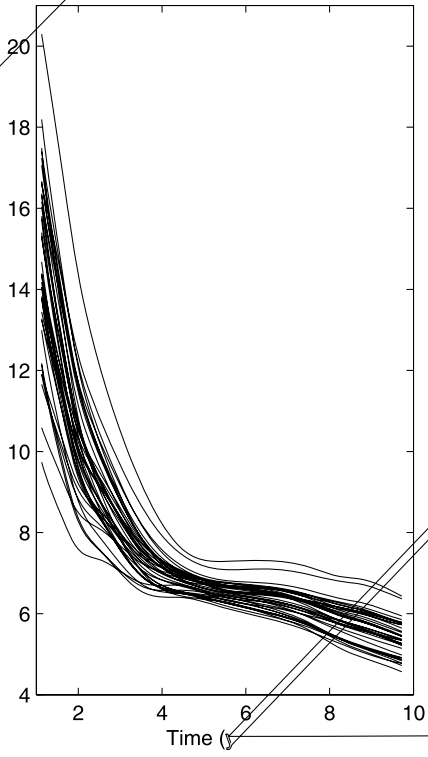
(1958), (1984), (1992), (1998), (2005)

18 ( ... ), 10 ( ... ), 39 ( ... )

Br 39 ( ... ), (1954), 10 ( ... ), 15 ( ... ), Br 39 {1, 1.25, 1.5, 1.75, 2, 3, 4, 5, 6, 7, 8, 8.5, 9, 9.5, 10},  $\{s_j\}_{j=1, \dots, 15}$ ,  $X_{ij} = (h_{i,j+1} - h_{ij}) / (t_{j+1} - t_j)$ ,  $h_{ij} = s_j$ ,  $t_j = (s_j + s_{j+1}) / 2$ ,  $i = 1, \dots, 39$ ,  $j = 1, \dots, 14$ . (2003), (2005).

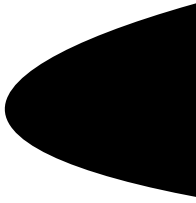
A Br 39 ( ... )







2 4 6 8 10 12 14 16 18 20  
Time (years)

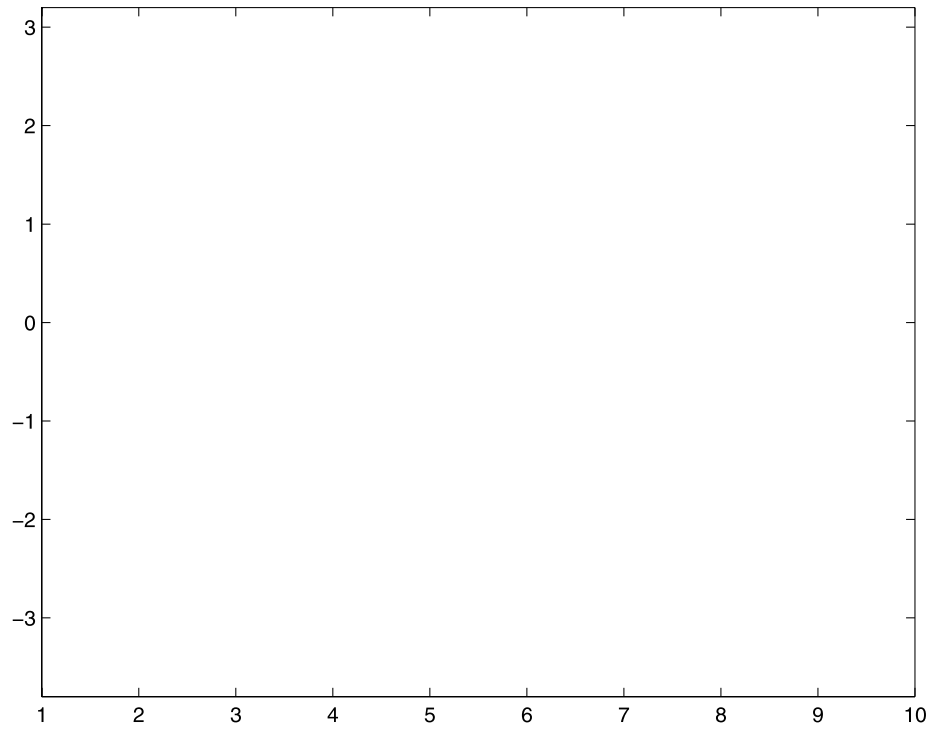


$= K_j \psi ( i,$

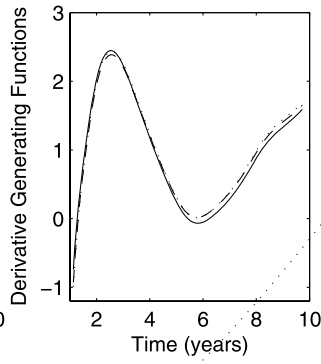
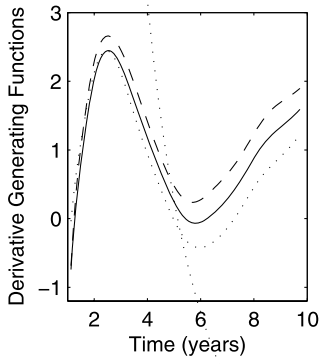
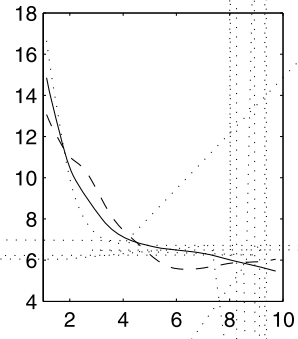
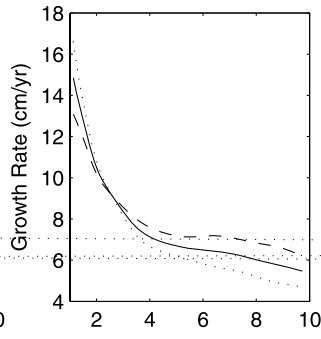
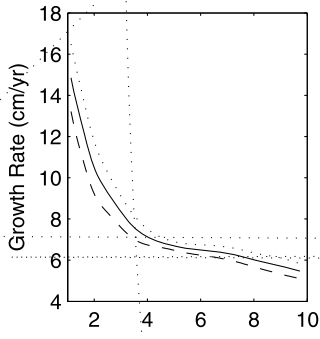
where  $g_i^*(t)z(t) dt = \sum_{j=1}^K \gamma_{X_i,j} z_j$ ,  $X_i$  is the derivative generating function of  $X_i$ ,  $K=3$ ,  $\gamma_{X_i,j}$  is the  $j$ -th derivative of  $X_i$  at  $t=0$ , and  $\psi_j(t)$  is the  $j$ -th derivative of  $\psi(t)$  at  $t=0$ .

$$(15) \quad \hat{g}_i^*(t) = \sum_{j=1}^K \gamma_{X_i,j} \hat{\psi}_j(t)$$

where  $\hat{\psi}_j(t) = \psi_j(t)$ . (3) (7).  $\hat{g}_i^*$  for  $K=3$  is given in (39) for  $X_i$  in (38).  $\hat{g}_i^*$  is the  $i$ -th derivative of  $\hat{g}^*$  at  $t=0$ .







m, r, m, m

5. Add a e, a d f

5.1. Bounds on P(||X-x|| <= u). P(||X-x|| <= u) ... u -> 0 ... (19)

g(x) X n (14)

X = \sum \xi\_j \psi\_j, r(\xi\_j) = \theta\_j, \theta\_j, j >= 1, \xi\_j

A ... B, \beta > 0, (16) ... \theta\_j = -Bj^\beta + o(j^\beta) ... j \to \infty,

\eta\_j = \xi\_j/\theta\_j^{1/2} \eta, ...

(17) B\_1 u^b \le P(|\eta| \le u) \le B\_2 u^b ... u > 0, P(|\eta| > u) \le B\_3 (1+u)^{-B\_4} ... u > 0, B\_1, \dots, B\_4, b > 0.

x=0, b, B, \beta ... (16) ... (17),

(18) \pi(u) \approx -\frac{b\beta}{\beta+1} \frac{2}{B} |u|^{(\beta+1)/\beta}

H 4. If (16) and (17) hold, then, with \pi(u) given by (18),

(19) P(||X|| \le u) = \pi(u)^{1+o(1)} as u \downarrow 0.

m 1, 3, \theta\_j (16), \xi\_j (12)

$$\begin{aligned} h^{2\alpha} &\asymp (-2\alpha| \cdot | h) \\ &\asymp -\{1 + o(1)\}2\alpha \frac{\beta + 1}{b\beta} \frac{B}{2}^{1/(\beta+1)} (\cdot, n)^{\beta/(\beta+1)}. \end{aligned}$$

Let  $\beta > 1$ . By (16) and (17), we have  $\theta_j = (-Bj^\beta)^{-1/\beta}$  for  $j = 1, \dots, \eta$ . Assume  $\beta = b = 1$ . Let  $\pi(u) = -c(\cdot, u)^{(\beta+1)/\beta} = -c(\cdot, u)^{2/\beta}$ , where  $c > 0$ . Then  $\pi(u) \asymp -c(\cdot, u)^{2/\beta}$  for  $u \neq 0$ . Let  $X = (X_1, \dots, X_\eta)$ .

By (19), we have  $P(\|X - x\| \leq u) \asymp u^{-c(\cdot, x)^{2/\beta}}$  for  $x = 0$  and  $u > 0$ . Let  $X_1 - X_2$ . By (19), we have  $P(\|X_1 - X_2 - x\| \leq u) \asymp u^{-c(\cdot, x)^{2/\beta}}$  for  $x = 0$  and  $u > 0$ . Let  $x = (\theta_j^{1/2} x_j, \dots, \theta_j^{1/2} x_j)$  for  $j = 1, \dots, \eta$ .

By (16), we have  $P(\|X - x\| \leq u) \asymp (-C_1 u^{-C_2})^{-1/\beta}$  for  $u > 0$  and  $x = 0$ . Let  $C_1, C_2 > 0$ . By (2003), we have  $P(\|X - x\| \leq u) \asymp (-C_1 u^{-C_2})^{-1/\beta}$  for  $u > 0$  and  $x = 0$ . Let  $C_3 > 0$ . By (2007), we have  $P(\|X - x\| \leq u) \asymp (-C_1 u^{-C_2})^{-1/\beta}$  for  $u > 0$  and  $x = 0$ .

Let  $\sigma^2 = \text{Var}(X_j)$  for  $j = 1, 2$ . Then  $N_2 \leq K(0)N_1$ , where  $K(\cdot) = \dots$

5.2. Proof of Theorem 1. Let  $\sigma^2 = \text{Var}(X_j)$  for  $j = 1, 2$ . Then  $N_2 \leq K(0)N_1$ , where  $K(\cdot) = \dots$

for  $x \in \mathbb{R}^d$  and  $\mathcal{X} = [0, c]$ . We have,

$$\begin{aligned}
 & E[\{\hat{g}(x) - g(x)\}^2 | \mathcal{X}] \\
 &= [E\{\hat{g}(x) | \mathcal{X}\} - g(x)]^2 + \text{var}(\hat{g}(x) | \mathcal{X}) \\
 (20) \quad &\leq \sum_{i=1, \dots, n} |g(X_i) - g(x)| I(\|X_i - x\| \leq ch) + \frac{\sigma^2 \sum_{i=1}^n K_i^2(x)}{(\sum_{i=1}^n K_i(x))^2} \\
 &\leq \sum_{y: \|y\| \leq ch} |g(x) - g(x+y)|^2 + \frac{\sigma^2 K(0)}{N_1}.
 \end{aligned}$$

Since  $g \in \mathcal{G}(C, x, \alpha)$ , (9) implies  $|g(x) - g(x+y)| \leq C\|y\|^\alpha$ . Using (20) and the fact that  $K_i(x) \geq K_i(x)I(\|X_i - x\| \leq c_1h) \geq K(c_1)I(\|X_i - x\| \leq c_1h)$ , we get  $c_1 \geq 1$  and (A2). Thus, (10) implies  $N_1^{-1} \rightarrow 0$  as  $n \rightarrow \infty$ . Since  $E(N_1^{-1}) \rightarrow 0$ , we get from (20),  $E[\{\hat{g}(x) - g(x)\}^2 | \mathcal{X}] \rightarrow 0$  as  $n \rightarrow \infty$ . Using (13) and (14), we get from (20)

$$\begin{aligned}
 E[\{\hat{g}(x) - g(x)\}^2 | \mathcal{X}] &\leq C^2(ch)^{2\alpha} + \frac{\sigma^2 K(0)}{N_1} \\
 &\leq C^2(ch)^{2\alpha} + \frac{\sigma^2 K(0)\{1 + o_p(1)\}}{K(c_1)nP(\|X - x\| \leq c_1h)}
 \end{aligned}$$

$$E(N_1^{-1}) \leq E[\{\sum_{i=1}^n I(\|X_i - x\| \leq c_1h)\}^{-1}] \asymp \{nP(\|X - x\| \leq c_1h)\}^{-1}.$$

5.3. Proof of Theorem 2.

Let  $f \in \mathcal{G}(C, 0, \alpha)$ ,  $x = 0$ . Let  $f$  be bounded on  $B_1$ ,  $B_2$ ,  $B_3$  and  $[-B_2, B_2]$ , where  $B_1, B_2, B_3$  are balls centered at 0. Let  $g_1 \equiv 0$  and  $g_2(y) = h^\alpha f(\|y\|/h)$ . Let  $\|y\| \leq h$ ,  $0 < \alpha \leq 1$ ,

$$\begin{aligned}
 |g_2(y) - g_2(0)| &= h^\alpha |f(\|y\|/h) - f(0)| \leq h^\alpha B_1 \|y\|/h \leq h^\alpha B_1 (\|y\|/h)^\alpha \\
 &= B_1 \|y\|^\alpha,
 \end{aligned}$$

and, if  $\|y\| > h$ ,

$$|g_2(y) - g_2(0)| \leq 2h^\alpha B_3 \leq 2B_3 \|y\|^\alpha.$$

Thus,  $g_2 \in \mathcal{G}(C, 0, \alpha)$  and  $(B_1, 2B_3) \leq C$ .

Let  $m \rightarrow \infty$  and  $n \rightarrow \infty$  such that  $m/n \rightarrow 0$  as  $n \rightarrow \infty$ .



is continuous.

$$(21) \quad P(\rho > 1) \rightarrow 0 \text{ as } n \rightarrow \infty.$$

Next,

$$2. \quad \rho = \frac{1}{n} \sum_{i=1}^n \{g_2(X_i)^2 - 2\varepsilon_i g_2(X_i)\},$$

$$\text{where } \mathcal{X}, \text{ and } \mathbf{r} \text{ are } \dots \text{ and } s_n^2 = \frac{1}{n} \sum_{i=1}^n g_2(X_i)^2 \dots$$

$$(22) \quad \lim_{B \rightarrow \infty} \lim_{n \rightarrow \infty} P(s_n^2 > B) = 0$$

...  $B_2$  ...  $0 < B \leq c_1$ , ...  $|g_2(x)| \leq B_3 h^\alpha I(\|x\| \leq c_1 h)$ ,

$$(23) \quad s_n^2 \leq B_3 h^{2\alpha} \sum_{i=1}^n I(\|X_i\| \leq c_1 h).$$

...  $nP(\|X\| \leq c_1 h) \rightarrow \infty$ ,

$$\frac{\sum_{i=1}^n I(\|X_i\| \leq c_1 h)}{nP(\|X\| \leq c_1 h)} \rightarrow 1$$

... (12) ... (23) ... (22).

5.4. Proof of Theorem 3. ...  $K_{i_1 i_2 j}$  ...  $K(i_1, i_2, j|x)$ . A ... (3)

$$(24) \quad K_{i_1 i_2 j} = 0, \dots \quad \|X_{i_1} - x\| \leq h_1, \quad \|X_{i_2} - x\| \leq h_1, \dots \quad Q_{i_1 i_2} \leq h_2.$$

...  $\delta > 0$ , ...  $s(\delta)$ , ...  $|g(x+y) - g(x) - g_x y|$ , ...  $\|y\| \leq \delta$ , ... A ... (3),

$$(25) \quad \delta^{-1} s(\delta) \rightarrow 0 \text{ as } \delta \downarrow 0.$$

$$\text{... } \varepsilon_{i_1 i_2}, \text{ ... } \|X_{i_k} - x\| \leq h_1, \text{ ... } k = 1, 2, \dots \varepsilon_{i_1 i_2}, \dots$$

$$|g(X_{i_1}) - g(X_{i_2}) - g_x(X_{i_1} - X_{i_2})| \leq 2s(h_1).$$

$$\text{... } \varepsilon_{i_1 i_2} = \varepsilon_{i_1} - \varepsilon_{i_2}, \text{ ... } \varepsilon_{i_1 i_2},$$

$$|Y_{i_1} - Y_{i_2} - \{g_x(X_{i_1} - X_{i_2}) + \varepsilon_{i_1 i_2}\}| \leq 2s(h_1).$$

By (24), we have

$$\begin{aligned}
 & \sum_{i_1, i_2}^{(j)} (Y_{i_1} - Y_{i_2}) K_{i_1 i_2 j} \\
 (26) \quad & - \sum_{i_1, i_2}^{(j)} K_{i_1 i_2 j} \sum_{k=1}^{\infty} \xi_{i_1 i_2 k} \gamma_{xk} + \sum_{i_1, i_2}^{(j)} \varepsilon_{i_1 i_2} K_{i_1 i_2 j} \\
 & \leq 2s(h_1) \sum_{i_1, i_2}^{(j)} K_{i_1 i_2 j}.
 \end{aligned}$$

Next,

$$\begin{aligned}
 (27) \quad & |\hat{\xi}_{i_1 i_2 j} - \xi_{i_1 i_2 j}| = |(X_{i_1} - X_{i_2})(\hat{\psi}_j - \psi_j)| \\
 & \leq \|X_{i_1} - X_{i_2}\| \|\hat{\psi}_j - \psi_j\| \leq 2h_1 \|\hat{\psi}_j - \psi_j\|,
 \end{aligned}$$

By (24), (26) and (27), we have

$$\begin{aligned}
 & \sum_{i_1, i_2}^{(j)} (Y_{i_1} - Y_{i_2}) K_{i_1 i_2 j} \\
 (28) \quad & - \gamma_{xj} \sum_{i_1, i_2}^{(j)} \hat{\xi}_{i_1 i_2 j} K_{i_1 i_2 j} \\
 & + \sum_{i_1, i_2}^{(j)} K_{i_1 i_2 j} \sum_{k: k \neq j} \xi_{i_1 i_2 k} \gamma_{xk} + \sum_{i_1, i_2}^{(j)} \varepsilon_{i_1 i_2} K_{i_1 i_2 j} \\
 & \leq 2\{s(h_1) + |\gamma_{xj}|h_1 \|\hat{\psi}_j - \psi_j\|\} \sum_{i_1, i_2}^{(j)} K_{i_1 i_2 j}.
 \end{aligned}$$

Next,

$$\begin{aligned}
 & \sum_{i_1, i_2}^{(j)} K_{i_1 i_2 j} \sum_{k: k \neq j} \xi_{i_1 i_2 k} \gamma_{xk} \\
 & = \sum_{i_1, i_2}^{(j)} K_{i_1 i_2 j} \sum_{k: k \neq j} \gamma_{xk} (X_{i_1} - X_{i_2}) \psi_k \\
 & \leq \sum_{i_1, i_2}^{(j)} K_{i_1 i_2 j} \delta.
 \end{aligned}$$

$$\leq \|g_x\| \sum_{i_1, i_2}^{(j)} K$$

(32) ...  $\hat{\gamma}_{xj}$  (7) ... (27)

$$\begin{aligned}
 (j) \sum_{i_1, i_2} \hat{\xi}_{i_1 i_2 j} K_{i_1 i_2 j} &\geq \sum_{i_1, i_2}^{(j)} m (0, \xi_{i_1 j} - \xi_{i_2 j} - 2h_1 \|\hat{\psi}_j - \psi_j\|) K_{i_1 i_2 j} \\
 (33) &\geq \sum_{i_1, i_2}^{(j)} m (0, \xi_{i_1 j} - \xi_{i_2 j}) K_{i_1 i_2 j} \\
 &\quad - 2h_1 \|\hat{\psi}_j - \psi_j\| \sum_{i_1, i_2}^{(j)} K_{i_1 i_2 j}.
 \end{aligned}$$

(j) ...  $\hat{\xi}_{i_1 i_2 j} > 0$  ...  $B > 0$

$$(34) \sum_{i_1, i_2}^{(j)} m (0, \xi_{i_1 j} - \xi_{i_2 j}) K_{i_1 i_2 j} \geq \{1 + o_p(1)\} B h_1 \sum_{i_1, i_2}^{(j)} K_{i_1 i_2 j}.$$

(j) ...  $n^{-1/2}/m$  ...  $(h_1, h_2) \rightarrow 0$  ... (3)

$$(35) \|\hat{\psi}_j - \psi_j\| = O_p(n^{-1/2}).$$

(33) (35) m

$$(36) \sum_{i_1, i_2}^{(j)} \hat{\xi}_{i_1 i_2 j} K_{i_1 i_2 j} \geq \{1 + o_p(1)\} B h_1 \sum_{i_1, i_2}^{(j)} K_{i_1 i_2 j}$$

(34) ... (7) ... (25), (32) ... (36)

$$(37) \hat{\gamma}_{xj} = \gamma_{xj} + O_p \left( \frac{\sum_{i_1, i_2}^{(j)} \varepsilon_{i_1 i_2} K_{i_1 i_2 j}}{h_1 \sum_{i_1, i_2}^{(j)} K_{i_1 i_2 j}} \right) + o_p(1).$$

(37) ...  $X_{i_1 i_2 j}$

$$O_p \left( h_1^2 \sum_{i_1, i_2}^{(j)} K_{i_1 i_2 j}^{-1} \right) = O_p[\{(nh_1)^2 E(k_{i_1 i_2 j})\}^{-1}] = o_p(1),$$

(37) m ...  $\hat{\gamma}_{xj} = \gamma_{xj} + o_p(1)$  ... m 3.

5.5. Proof of Theorem 4. For  $t \in (0, 1)$  and  $D_t = (\theta_j^{1-t})^{-1}$ ,

$$(38) \quad P(\|X\| \leq u) = P \left( \prod_{j=1}^{\infty} \theta_j \eta_j^2 \leq u^2 \right) \leq \prod_{j=1}^{\infty} P(\theta_j \eta_j^2 \leq u^2),$$

$$\geq \prod_{j=1}^{\infty} P(\theta_j^t \eta_j^2 \leq D_t u^2),$$

where  $\theta_j = \theta_j^{1-t} (\theta_j^t \eta_j^2 - D_t u^2) \leq 0$

$$P \left( \prod_{j=1}^{\infty} \theta_j \eta_j^2 \leq u^2 \right) = P \left( \prod_{j=1}^{\infty} \theta_j^{1-t} (\theta_j^t \eta_j^2 - D_t u^2) \leq 0 \right)$$

$$\geq P(\theta_j^t \eta_j^2 \leq D_t u^2 \text{ for } j \leq J).$$

Let  $J = J(u)$  be such that  $u/\theta_j^{1/2} \leq \zeta$ , where  $\zeta$  is the smallest  $m$  such that  $B_1 u^b \leq P(|\eta| \leq u) \leq B_2 u^b$  for  $0 \leq u \leq \zeta$ .

$$(39) \quad P(\theta_j \eta_j^2 \leq u^2) \leq \prod_{j=1}^J P(|\eta| \leq u \theta_j^{-1/2})$$

$$= u^{bJ} \prod_{j=1}^J \left( \frac{1}{2} b B j^\beta + o(J^{\beta+1}) \right)$$

$$\asymp -\frac{bB\beta}{2(\beta+1)} J^{\beta+1} + o(J^{\beta+1})$$

$$= \pi(u)^{1+o(1)}$$

As  $u \downarrow 0$ ,  $\pi(u) \rightarrow 0$  (18).

Let  $J = J(u)$  be such that  $D_t^{1/2} u / \theta_j^{t/2} \leq \zeta$ . From (39), we have

$$(40) \quad \prod_{j=1}^J P(\theta_j^t \eta_j^2 \leq D_t u^2)$$

$$\asymp -\frac{b\beta}{\beta+1} \frac{2}{Bt} u^{1/\beta} | \dots u |^{(\beta+1)/\beta} + o(| \dots u |^{(\beta+1)/\beta})$$

$$= \pi(u)^{t^{-1/\beta} + o(1)}.$$

As  $j \geq J + 1$ ,

$\pi$

Let  $B_5 = B_5(t) \in (0, 1)$ ,  $\pi_j \in (0, B_5)$  for  $j \geq J+1$ ,

$$1 - \pi_j \geq \sum_{k=1}^{\infty} \frac{\pi_j^k}{k} \geq -B_6 \pi_j$$

for  $m \geq J+1$ .

$$\sum_{j=J+1}^{\infty} (1 - \pi_j) \geq -B_6 \sum_{j=J+1}^{\infty} \pi_j \geq -B_7 \sum_{j=J+1}^{\infty} (\theta_j^{t/2}/u)^{B_4},$$

where  $B_6 = B_6(t) > 0$  and  $B_7 = B_7(t) > 0$  for  $t \in (0, 1)$ . From (40), (41) and (42), we have  $\pi_j \leq B_8 \theta_j^{t/2}/u$  for  $j \geq J+1$ , where  $B_8 = B_8(t) > 0$  for  $t \in (0, 1)$ . Thus,  $\pi_j \leq B_8 \theta_j^{t/2}/u$  for  $j \geq J+1$ , where  $B_8 = B_8(t) > 0$  for  $t \in (0, 1)$ .

$$(42) \quad \sum_{j=1}^{\infty} P(\theta_j^t \eta_j^2 \leq D_t u^2) = \pi(u)^{1+o(1)},$$

where  $\pi(u)$  is defined in (19).

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