



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. In this paper, we consider the case where  $g$  is a linear function, that is,  $g(x) = a + bx$ , where  $a$  and  $b$  are constants, and  $\varepsilon$  is a random variable with mean zero and variance  $n^{-1/2}$ . The asymptotic properties of the maximum likelihood estimator of  $a$  and  $b$  are studied in (1991), (2002), (2003), (2003), (2003), (2005), (2005), (2005) and (2007).

In this paper, we study the asymptotic properties of the maximum likelihood estimator of  $a$  and  $b$  in the case where  $\varepsilon$  is a random variable with mean zero and finite variance. The asymptotic properties of the maximum likelihood estimator of  $a$  and  $b$  are studied in (1998) and (2002). The asymptotic properties of the maximum likelihood estimator of  $a$  and  $b$  are studied in (2003, 2004, 2006) and (2007).

Let  $\psi_1, \psi_2, \dots$  be a complete orthonormal system in  $L_2(\mathcal{I})$ . Then 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 constants. The asymptotic properties of the maximum likelihood estimator of  $a$  and  $b$  are studied in (2007).



is a  $\mathcal{M}$ -valued function on  $K$  such that  $g(x) = \sum_{j=1}^{\infty} \gamma_{xj} t_j$  for all  $x \in K$ . (7)

Let  $\mathcal{M}$  be a  $\mathcal{M}$ -valued function on  $K$  such that  $\mathcal{M}(x) = \sum_{j=1}^{\infty} \gamma_{xj} t_j$  for all  $x \in K$ . (8)

Let  $\mathcal{M}$  be a  $\mathcal{M}$ -valued function on  $K$  such that  $\mathcal{M}(x) = \sum_{j=1}^{\infty} \gamma_{xj} t_j$  for all  $x \in K$ . (9)

Let  $\mathcal{M}$  be a  $\mathcal{M}$ -valued function on  $K$  such that  $\mathcal{M}(x) = \sum_{j=1}^{\infty} \gamma_{xj} t_j$  for all  $x \in K$ . (10)

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

as  $\delta \rightarrow 0$ . Let  $\mathcal{M}$  be a  $\mathcal{M}$ -valued function on  $K$  such that

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

where  $\gamma_{xj} = g_x \psi_j$  for all  $x \in K$  and  $t_j$  is a  $\mathcal{M}$ -valued function on  $K$ . Let  $y = \sum_{j=1}^{\infty} y_j t_j$  and  $\mathcal{M}(y) = \sum_{j=1}^{\infty} \gamma_{xj} t_j$  for all  $x \in K$ . (11)

Let  $\mathcal{M}$  be a  $\mathcal{M}$ -valued function on  $K$  such that  $\mathcal{M}(x) = \sum_{j=1}^{\infty} \gamma_{xj} t_j$  for all  $x \in K$ . (12)

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

where  $\hat{\psi}_j$  is the kernel estimator of  $\psi_j$ .

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

Assume  $\sum_{i_1, i_2}^{(j)} \hat{\xi}_{i_1 i_2 j} > 0$ ,

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

where  $K$  is a kernel function,  $h_1, h_2$  are bandwidths,  $Q_{i_1 i_2 j}$  is a weight function,  $X_{i_1}, X_{i_2}$  are random variables,  $\hat{\psi}_j$  is the kernel estimator of  $\psi_j$ ,  $\hat{\gamma}_{xj}$  is the kernel estimator of  $\gamma_{xj}$ ,  $h_1, h_2$  are bandwidths.

### 3. Theoretical results

#### 3.1. Consistency and convergence rates of estimators of $g$ .

##### 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  $n \rightarrow \infty$ ,  $nP(\|X - x\| \leq c_1 h) \rightarrow \infty$  as  $n \rightarrow \infty$ ,

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

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

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

Let  $\mathcal{X} = \{X_1, \dots, X_n\}$  be a random sample of  $X$ .

**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) and (13), we can write  $Y_i = Y_i(g) = g(X_i) + \varepsilon_i$ ,  $1 \leq i < \infty$ , where  $\varepsilon_i$  are independent and identically distributed random variables with mean zero and variance  $\sigma^2$ . Let  $Y_i = Y_i(g) = g(X_i) + \varepsilon_i$ ,  $1 \leq i < \infty$ . Let  $\mathcal{X} = \{X_1, \dots, X_n\}$ . **5.1. Consistency of the estimator.** From (12), we can write  $h^{2\alpha} P(\|X - x\| \leq c_1 h) \asymp n^{-1}$ . A moment calculation (see (2007) for details) shows that  $P(\|X - x\| \leq c_1 h) \asymp n^{-1} h^{-2\alpha}$ . (14) implies 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 write  $Y_i = Y_i(g) = g(X_i) + \varepsilon_i$ ,  $1 \leq i < \infty$ . Let  $\mathcal{X} = \{X_1, \dots, X_n\}$ . **5.1. Consistency of the estimator.** From (12), we can write  $h^{2\alpha} P(\|X - x\| \leq c_1 h) \asymp n^{-1}$ . A moment calculation (see (2007) for details) shows that  $P(\|X - x\| \leq c_1 h) \asymp n^{-1} h^{-2\alpha}$ . (14) implies that

**3.2. Consistency of derivative estimator.** Let  $\hat{\gamma}_{xj}$  be the derivative estimator of  $\gamma_j(x)$  defined by

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

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)  $h_1, h_2 \rightarrow 0$ ,  $n h_1 \rightarrow \infty$ ,  $n^{1/2} m(h_1, h_2) \rightarrow \infty$ ,  $(n h_1)^2 E(k_{i_1 i_2 j}) \rightarrow \infty$ .

Let  $X = (X_1, \dots, X_p)^\top \in \mathbb{R}^p$ ,  $V = (V_1, \dots, V_p)^\top \in \mathbb{R}^p$ ,  $\psi_j = (\psi_{j1}, \dots, \psi_{jp})^\top \in \mathbb{R}^p$ ,  $\hat{\psi}_j = (\hat{\psi}_{j1}, \dots, \hat{\psi}_{jp})^\top \in \mathbb{R}^p$ . By Assumption 4(1),  $\|\hat{\psi}_j - \psi_j\| = o_p(n^{-1/2})$ .

Let  $X = (X_1, \dots, X_p)^\top \in \mathbb{R}^p$ ,  $\psi_j = (\psi_{j1}, \dots, \psi_{jp})^\top \in \mathbb{R}^p$ ,  $\hat{\psi}_j = (\hat{\psi}_{j1}, \dots, \hat{\psi}_{jp})^\top \in \mathbb{R}^p$ . By Assumption 4(1),  $\|\hat{\psi}_j - \psi_j\| = o_p(n^{-1/2})$ . Let  $\theta_j = (\theta_{j1}, \dots, \theta_{jp})^\top \in \mathbb{R}^p$ . By Assumption 3(1),  $n^{-\varepsilon} = O(h_j)$  for  $j = 1, 2, \dots$ ,  $\varepsilon > 0$ . Let  $C_1 > 0$ . By Assumption 3(1),  $n h_1 P(\|x - X\| \leq C_2 h_1) \rightarrow \infty$  as  $h_1 \rightarrow 0$ ,  $C_2 > 0$ . By Assumption 3(1),  $n h^{C_1+1} \rightarrow \infty$  as  $h \rightarrow 0$ ,  $C_1 > 0$ . By Assumption 3(2),  $h_1 \rightarrow 0$ . By Assumption 3(1),  $n P(q_{12j} \leq h_2) = O(h_2^{C_1})$  as  $h_2 \rightarrow 0$ ,  $C_1 > 0$ . By Assumption 3(1),  $n P(q_{12j} \leq C_2 h_2) \rightarrow \infty$  as  $h_2 \rightarrow 0$ ,  $C_2 > 0$ .

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),  $e = \sum_{j=1}^{j_0} e_j \gamma_{xj}$ . By Assumption 3,  $a_j = e_j$ ,  $1 \leq j \leq j_0$ ,  $a_j = 0$ ,  $j > j_0$ . By Assumption 3,  $\hat{g}_x e = \sum_{j=1}^{j_0} e_j \hat{\gamma}_{xj}$ . By Assumption 3,  $\hat{g}_x e \rightarrow g_x e$  as  $h \rightarrow 0$ . By Assumption 3,  $\hat{g}_x a = \sum_{j=1}^{j_0} \hat{\gamma}_{xj} a_j$  as  $h \rightarrow 0$ . By Assumption 3,  $\hat{g}_x a \rightarrow g_x a$  as  $h \rightarrow 0$ .

By Assumption 3,  $\hat{g}_x a = \sum_{j=1}^{j_0} \hat{\gamma}_{xj} a_j$  as  $h \rightarrow 0$ . By Assumption 3,  $\hat{g}_x a \rightarrow g_x a$  as  $h \rightarrow 0$ .

Let  $r(n, x) = \sum_{j=1}^m \gamma_{xj} a_j$ , where  $\gamma_{xj} = \frac{a_j}{\sum_{j=1}^m a_j}$ . Assume  $\sum_{j=1}^m \gamma_{xj}^2 < \infty$ ,  $\|a\| < \infty$ ,  $r(n, x) \rightarrow \infty$  as  $n \rightarrow \infty$ ;  $\|a\| < \infty$ ,  $\hat{g}_x - g_x a \rightarrow 0$  as  $n \rightarrow \infty$ ;  $\lim_{n \rightarrow \infty} \hat{g}_x = g_x$ . Then  $\lim_{n \rightarrow \infty} r(n, x) = r(x)$ , where  $r(x) = \sum_{j=1}^m \gamma_{xj} a_j$ . Assume  $\lim_{n \rightarrow \infty} r(n, x) = r(x)$ , where  $r(x) = \sum_{j=1}^m \gamma_{xj} a_j$ . Assume  $\lim_{n \rightarrow \infty} r(n, x) = r(x)$ , where  $r(x) = \sum_{j=1}^m \gamma_{xj} a_j$ .

4. A cat effect a de at e et at t g t data.

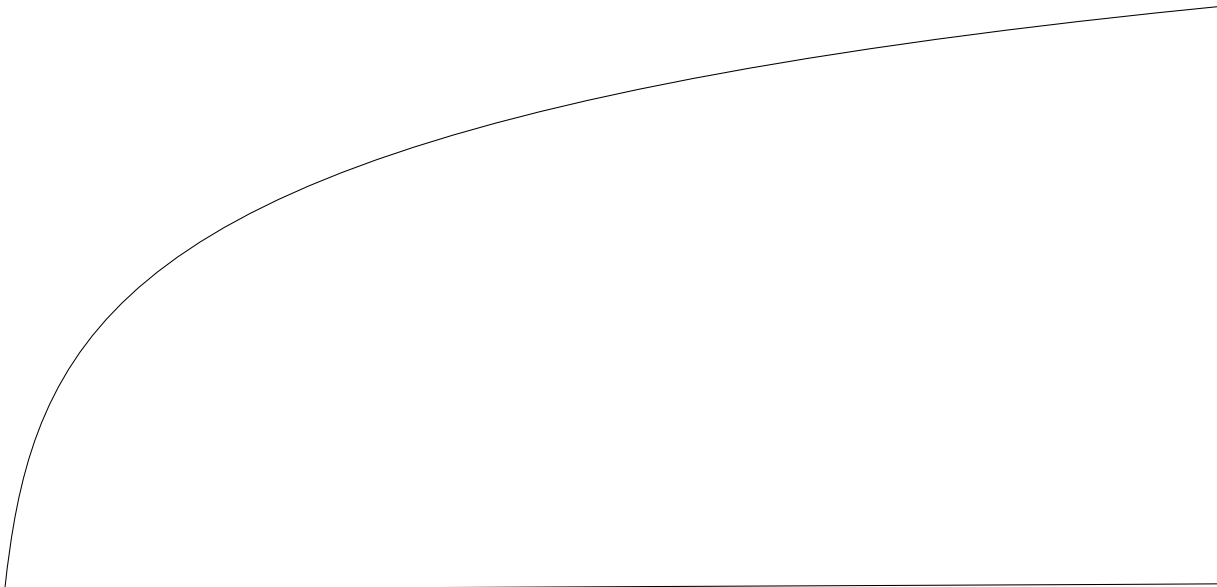
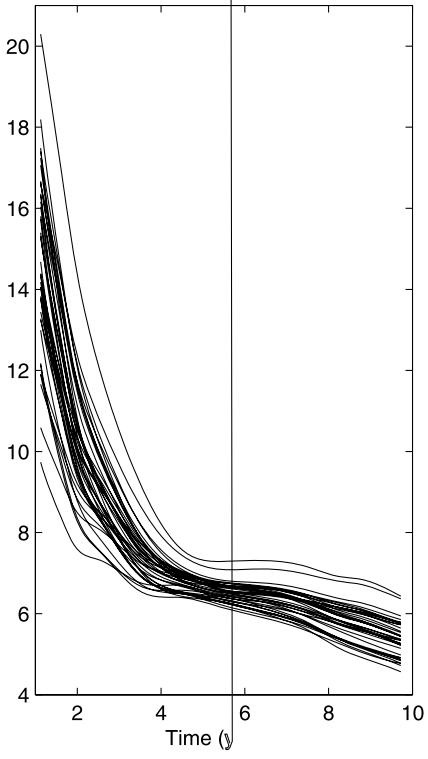
Let  $r(n, x) = \sum_{j=1}^m \gamma_{xj} a_j$ , where  $\gamma_{xj} = \frac{a_j}{\sum_{j=1}^m a_j}$ . Assume  $\sum_{j=1}^m \gamma_{xj}^2 < \infty$ ,  $\|a\| < \infty$ ,  $r(n, x) \rightarrow \infty$  as  $n \rightarrow \infty$ ;  $\|a\| < \infty$ ,  $\hat{g}_x - g_x a \rightarrow 0$  as  $n \rightarrow \infty$ ;  $\lim_{n \rightarrow \infty} \hat{g}_x = g_x$ . Then  $\lim_{n \rightarrow \infty} r(n, x) = r(x)$ , where  $r(x) = \sum_{j=1}^m \gamma_{xj} a_j$ . Assume  $\lim_{n \rightarrow \infty} r(n, x) = r(x)$ , where  $r(x) = \sum_{j=1}^m \gamma_{xj} a_j$ .

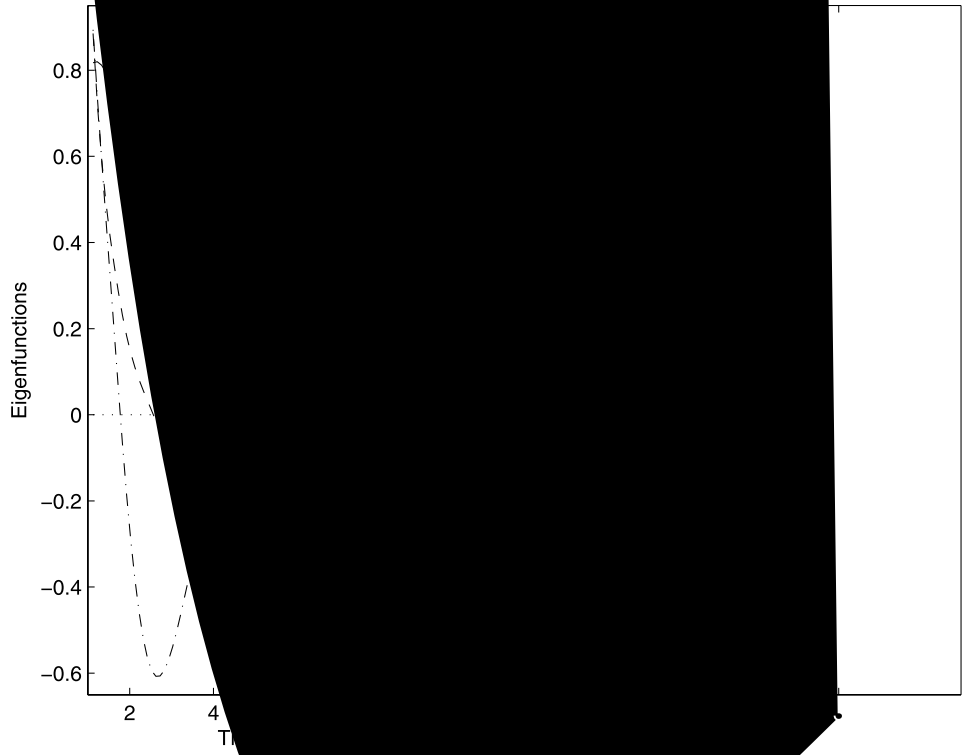
Let  $r(n, x) = \sum_{j=1}^m \gamma_{xj} a_j$ , where  $\gamma_{xj} = \frac{a_j}{\sum_{j=1}^m a_j}$ . Assume  $\sum_{j=1}^m \gamma_{xj}^2 < \infty$ ,  $\|a\| < \infty$ ,  $r(n, x) \rightarrow \infty$  as  $n \rightarrow \infty$ ;  $\|a\| < \infty$ ,  $\hat{g}_x - g_x a \rightarrow 0$  as  $n \rightarrow \infty$ ;  $\lim_{n \rightarrow \infty} \hat{g}_x = g_x$ . Then  $\lim_{n \rightarrow \infty} r(n, x) = r(x)$ , where  $r(x) = \sum_{j=1}^m \gamma_{xj} a_j$ . Assume  $\lim_{n \rightarrow \infty} r(n, x) = r(x)$ , where  $r(x) = \sum_{j=1}^m \gamma_{xj} a_j$ .

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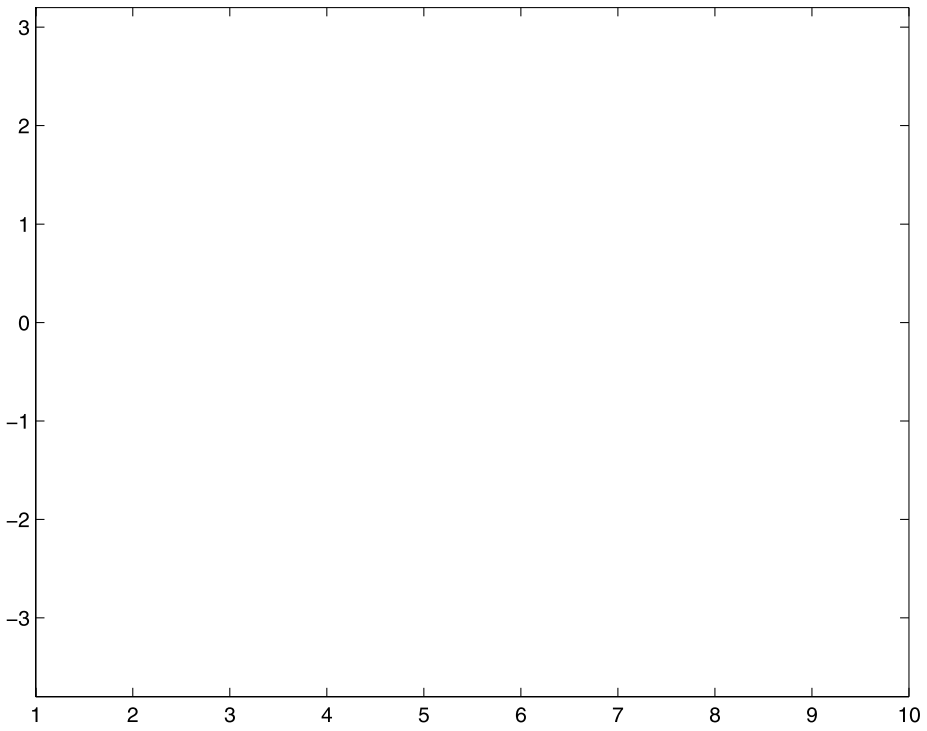


$$= K_j \psi ( i,$$

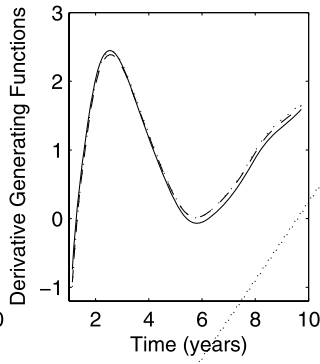
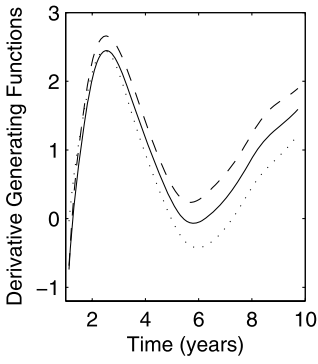
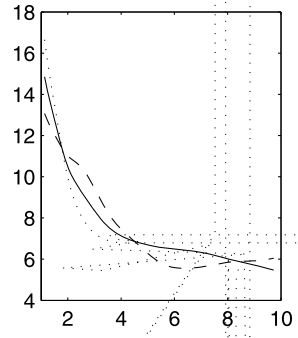
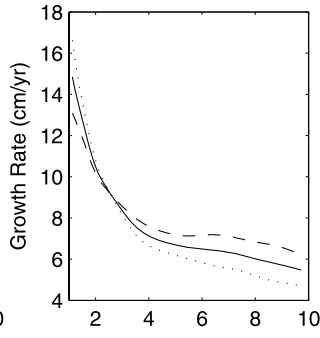
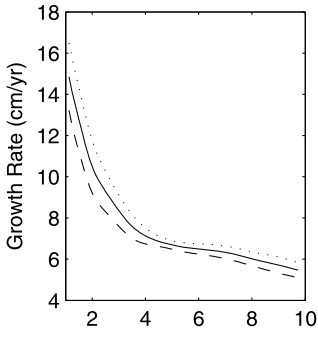
$g_i^*(t)z(t) dt = \sum_{j=1}^K \gamma_{X_i,j} z_j$ ,  $X_i$   $g_i^*$  derivative generating function.  $X_i$ .  $K=3$ .

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

$\gamma_{X_i,j} \psi_j(t)$  (3) (7).  $\hat{g}_i^*$   $K=3$   $X_i$   $\hat{\psi}_j(t)$ .







.....

**5. Add t a e t a d f .**

5.1. *Bounds on  $P(\|X-x\| \leq u)$ .* .....  
 $P(\|X-x\| \leq u) \dots u \rightarrow 0 \dots \dots \dots \hat{g}(x)$   
 $g(x) \dots \dots \dots (19) \dots \dots \dots (14)$   
 $X \dots \dots \dots n.$

$X$  .....  
 $X = \dots \xi_j \psi_j, \dots r(\xi_j) = \theta_j \dots \dots \theta_j, j \geq 1,$   
 $\xi_j \dots \dots j \dots \dots$

**A** .....  $B, \beta > 0,$   
 $(16) \dots \dots \theta_j = -Bj^\beta + o(j^\beta) \dots \dots j \rightarrow \infty,$

$\eta_j = \xi_j / \theta_j^{1/2} \dots \dots$   
 $\eta, \dots \dots$   
 $B_1 u^b \leq P(|\eta| \leq u) \leq B_2 u^b \dots \dots u > 0,$   
 $(17) \dots \dots P(|\eta| > u) \leq B_3 (1+u)^{-B_4} \dots \dots u > 0, \dots \dots B_1, \dots, B_4, b > 0.$

$x=0, \dots \dots b, B \dots \beta \dots (16) \dots (17), \dots$   
 $(18) \dots \dots \pi(u) \asymp -\frac{b\beta}{\beta+1} \frac{2}{B} |u|^{(\beta+1)/\beta} \dots \dots$

**H** ..... **4.** *If (16) and (17) hold, then, with  $\pi(u)$  given by (18),*  
 $(19) \dots \dots P(\|X\| \leq u) = \pi(u)^{1+o(1)} \dots \dots as u \downarrow 0.$

$m \dots \dots 1 \dots 3, \dots \dots \theta_j \dots \dots (16), \dots \dots \xi_j \dots \dots (12) \dots \dots$

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

Let  $\beta, \eta, \theta_j = (-Bj^\beta)$ ,  $\eta = 4$ ,  $\{\phi_j\}$ ,  $\beta = b = 1$ ,  $\pi(u) \asymp \{-c(|\cdot|u)^{(\beta+1)/\beta}\} = u^{-c(|\cdot|u)^{1/\beta}}$ ,  $c > 0$ ,  $\eta = 0$ .

Lemma 4. For  $x = 0$ ,  $P(\|X - x\| \leq u)$ ,  $u > 0$ ,  $X_1 - X_2$ ,  $P(\|X_1 - x\| \leq u)$  for  $x = \theta_j^{1/2} x_j$ .

(16),  $P(\|X - x\| \leq u) \asymp (-C_1 u^{-C_2})$ ,  $C_1, C_2 > 0$ ,  $x = 0$ , (2003), (1952),  $u^{C_3} \asymp (-C_1 u^{-C_2})$ ,  $C_3 > 0$ , (2007).

5.2. Proof of Theorem 1.  $\sigma^2$ , (1),  $N_j = \sum_i K_i(x)^j$ ,  $j = 1, 2$ ,  $N_2 \leq K(0)N_1$ ,  $K(\cdot)$

where  $m = m_n \rightarrow \infty$  as  $n \rightarrow \infty$  and  $0 < c_1 \leq c_2 < \infty$ .

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

By (9) and (20), we have  $E\{\hat{g}(x) | \mathcal{X}\} - g(x) = \sum_{i=1}^n \{K_i(x) - K_i(x)I(\|X_i - x\| \leq c_1h)\} / \sum_{i=1}^n K_i(x) \leq K(c_1)I(\|X - x\| \leq c_1h)$ , where  $K(c_1) = \sup_{\|y\| \leq c_1h} |g(x) - g(x+y)|$ . By (A2), (10) and  $N_1^{-1} \rightarrow 0$  as  $n \rightarrow \infty$ , we have  $E(N_1^{-1}) \rightarrow 0$ . By (20), (13) and (14), we have  $E\{\hat{g}(x) - g(x)\}^2 | \mathcal{X} \leq C^2(ch)^{2\alpha} + \frac{\sigma^2 K(0)}{N_1}$ .

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

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

### 5.3. Proof of Theorem 2.

Let  $f$  be a function satisfying (A1) and (A2) with  $x = 0$ . Let  $f$  be bounded on  $B_1$ ,  $B_2$  and  $B_3$ , where  $B_1 = [-B_1, B_1]$ ,  $B_2 = [-B_2, B_2]$  and  $B_3 = [-B_3, B_3]$ . Let  $g_1 \equiv 0$  and  $g_2(y) = h^\alpha f(\|y\|/h)$ . Let  $\|y\| \leq h$  and  $0 < \alpha \leq 1$ ,

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

if  $\|y\| > h$ ,

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

Thus,  $g_2 \in \mathcal{G}(C, 0, \alpha)$  for some  $C = C(B_1, 2B_3) < \infty$ .

Let  $\mathcal{X} = \{X_i\}_{i=1}^n$  and  $\mathcal{Y} = \{Y_i\}_{i=1}^n$  be independent random samples from  $X \sim N(0, \Sigma)$  and  $Y \sim N(0, \Sigma)$ , respectively, where  $\Sigma = \text{diag}(\sigma_1^2, \dots, \sigma_p^2)$ .



(21)  $P(\rho > 1) \rightarrow 0$  as  $n \rightarrow \infty$ .

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

where  $s_n^2 = \frac{1}{n} \sum_{i=1}^n g_2(X_i)^2$  and  $\varepsilon_i = 4s_n^2 \dots$  (21)

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

where  $B_2$  is a constant and  $f$  is a function such that  $0 < B \leq c_1$  and  $|g_2(x)| \leq B_3 h^\alpha I(\|x\| \leq c_1 h)$ ,

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

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

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

where  $\dots$  (12) and (23) are used in (22).

5.4. Proof of Theorem 3. Let  $K_{i_1 i_2 j} = K(i_1, i_2, j|x)$ . Assume (3.6) holds.

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

Let  $\delta > 0$ ,  $s(\delta)$  is a function such that  $|g(x+y) - g(x) - g_x y| \leq s(\delta)$  for  $\|y\| \leq \delta$ . Assume (3.6),

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

Let  $\varepsilon_{i_1 i_2} = \{g(X_{i_1}) - g(X_{i_2}) - g_x(X_{i_1} - X_{i_2})\}$  and  $\|X_{i_k} - x\| \leq h_1$ ,  $k = 1, 2$ . Let  $\varepsilon_{i_1 i_2} = \dots$ ,

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

Let  $\varepsilon_{i_1 i_2} = \varepsilon_{i_1} - \varepsilon_{i_2}$  and let  $\varepsilon_{i_1 i_2} = \dots$ ,

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

By (24), we have  $\xi_{i_1 i_2 j} = \xi_{i_1 j} - \xi_{i_2 j}$ , and  $g_x(X_{i_1} - X_{i_2}) = \sum_k \xi_{i_1 i_2 k} \gamma_{xk}$ .

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

By (24),

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

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

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

By (24),

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

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

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

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

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

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

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

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

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

And, for  $j \geq J+1$ ,

$$\pi o(\dots)$$

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

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

and moreover

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

where  $B_6, B_7$  are constants depending on  $\theta_j$  and  $B_4$ . From (40), we have  $\sum_{j=J+1}^{\infty} (\theta_j^{t/2}/u)^{B_4} \rightarrow 0$  as  $t \in (0, 1)$  and  $u \rightarrow 0$ . From (40), we have  $\sum_{j=J+1}^{\infty} (\theta_j^{t/2}/u)^{B_4} \rightarrow 0$  as  $u \rightarrow 0$ .

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

Therefore, (38), (39) and (42) imply (19).

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