

Functional Additive Models

MA

Consider a regression model with a single predictor X and a response Y . The model is assumed to be additive, meaning that the effect of X on Y is independent of the value of Y . This is often written as $E(Y|X) = \mu + \beta X$, where μ is the intercept and β is the slope. The additive model is a special case of the more general functional additive model, which allows for non-linear relationships between X and Y .

The functional additive model is defined by the equation $E(Y|X) = \mu + \beta X + \gamma(X)$, where $\gamma(X)$ is a function that captures the non-linear relationship between X and Y . The function $\gamma(X)$ is assumed to be smooth and bounded.

1.

Let X and Y be random variables with joint density function $f(x, y)$. The marginal density function of X is $f_X(x) = \int_{-\infty}^{\infty} f(x, y) dy$. The marginal density function of Y is $f_Y(y) = \int_{-\infty}^{\infty} f(x, y) dx$. The joint density function $f(x, y)$ is assumed to be smooth and bounded. The functional additive model is defined by the equation $E(Y|X) = \mu + \beta X + \gamma(X)$, where $\gamma(X)$ is a function that captures the non-linear relationship between X and Y . The function $\gamma(X)$ is assumed to be smooth and bounded.

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$$Y = \beta + \zeta_m \quad (1)$$

where β is a constant and ζ_m is a random variable with a probability density function $f_{\zeta_m}(z)$ for $z \in \mathbb{R}$. The random variable ζ_m is independent of X . The random variable Y is a function of X and ζ_m . The random variable Y is a function of X and ζ_m .

3. A A

Let $f_k(\cdot)$ be the probability density function of X for $k = 1, \dots, M$. Let $f_{km}(\cdot)$ be the probability density function of Y for $k = 1, \dots, M$ and $m = 1, \dots, M$. Let $f_k(\cdot)$ be the probability density function of X for $k = 1, \dots, M$. Let $f_{km}(\cdot)$ be the probability density function of Y for $k = 1, \dots, M$ and $m = 1, \dots, M$.

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$$E(Y - Y|k) = b_k \quad E(\zeta_m|k) = b_{km} \quad (2)$$

where b_k and b_{km} are constants. Let $f_k(\cdot)$ be the probability density function of X for $k = 1, \dots, M$. Let $f_{km}(\cdot)$ be the probability density function of Y for $k = 1, \dots, M$ and $m = 1, \dots, M$.

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$$E(Y|X) = Y + \sum_{k=1}^{\infty} f_k(k) \quad (3)$$

$$E(Y(t)|X) = Y(t) + \sum_{k=1}^{\infty} \sum_{m=1}^{\infty} f_{km}(k) m(t), \quad (4)$$

$$E f_k(k) = \dots, \quad k = 1, \dots, M \quad (5)$$

$$E f_{km}(k) = \dots, \quad k = 1, \dots, M, m = 1, \dots, M \quad (6)$$

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$$E(Y - Y|k) = E\{E(Y - Y|X)|k\} = E\left\{\sum_{j=1}^{\infty} f_j(j)|k\right\} = f_k(k), \quad (7)$$

$$E(\zeta_m|k) = E\{E(\zeta_m|X)|k\} = E\left\{\sum_{j=1}^{\infty} f_{jm}(j)|k\right\} = f_{km}(k). \quad (8)$$

$$E(\zeta_m|k) = f_{km}(k) = E(Y - Y|k) = f_{km}(k) = \dots, \quad k, m = 1, \dots, M \quad (9)$$

Let $f_k(\cdot)$ be the probability density function of X for $k = 1, \dots, M$. Let $f_{km}(\cdot)$ be the probability density function of Y for $k = 1, \dots, M$ and $m = 1, \dots, M$.

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4. A A

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$$\sum_{i=1}^n K \left(\frac{\hat{ik} - x}{h_k} \right) \{Y_i - \beta - \beta(x - \hat{ik})\} \quad (10)$$

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$$\{\hat{\xi}_{im}\}_{i=1, \dots, n} \quad (1)$$

$$\sum_{i=1}^n K \left(\frac{\hat{ik} - x}{h_{mk}} \right) \{\hat{\xi}_{im} - \beta - \beta(x - \hat{ik})\} \quad (2)$$

$$\hat{\beta} = \beta, \quad \hat{f}_{mk}(x) = \hat{\beta}(x) \quad M(1)$$

$$\hat{E}(Y|X) = \bar{Y} + \sum_{k=1}^K \hat{f}_k(x) \quad (3)$$

R = - \frac{\sum_{i=1}^n \{Y_i - E(Y_i|X_i)\}}{\sum_{i=1}^n (Y_i - \bar{Y})} \quad (4)

$$\hat{R} = - \frac{\sum_{i=1}^n \{Y_i - \hat{E}(Y_i|X_i)\}}{\sum_{i=1}^n (Y_i - \bar{Y})}, \quad (5)$$

$$E(Y_i|X_i) = \hat{E}(Y_i|X_i) \quad (6)$$

$$\hat{E}\{Y(t)|X\} = \hat{Y}(t) + \sum_{m=1}^M \sum_{k=1}^K \hat{f}_{mk}(x) \hat{m}(t), \quad t \in \mathcal{T}, \quad (7)$$

$$R = - \frac{\sum_{i=1}^n \int [Y_i(t) - E\{Y_i(t)|X_i\}] dt}{\sum_{i=1}^n \int \{Y_i(t) - \bar{Y}(t)\} dt}, \quad (8)$$

$$\hat{R} = - \frac{\sum_{i=1}^n \sum_{l=1}^{m_i} [V_{il} - \hat{E}\{Y_i(t_{il})|X_i\}] (t_{il} - t_{i,l-})}{\sum_{i=1}^n \sum_{l=1}^{m_i} \{V_{il} - \bar{Y}(t_{il})\} (t_{il} - t_{i,l-})} \quad (9)$$

$$\hat{E}\{Y_i(t)|X_i\} = \hat{E}\{Y_i(t)|X_i\} \quad (10)$$

5. A

E

$\hat{ik}, \hat{\xi}_{im}, \hat{\xi}_{im}, k = 1, \dots, K, m = 1, \dots, M,$

$\hat{f}_k, \hat{f}_{km},$

$\hat{\beta}, \hat{\beta},$

$\hat{E}(Y|X) = \bar{Y} + \sum_{k=1}^K \hat{f}_k(x)$

$\hat{E}\{Y(t)|X\} = \hat{Y}(t) + \sum_{m=1}^M \sum_{k=1}^K \hat{f}_{mk}(x) \hat{m}(t)$

$R = - \frac{\sum_{i=1}^n \int [Y_i(t) - E\{Y_i(t)|X_i\}] dt}{\sum_{i=1}^n \int \{Y_i(t) - \bar{Y}(t)\} dt}$

$\hat{R} = - \frac{\sum_{i=1}^n \sum_{l=1}^{m_i} [V_{il} - \hat{E}\{Y_i(t_{il})|X_i\}] (t_{il} - t_{i,l-})}{\sum_{i=1}^n \sum_{l=1}^{m_i} \{V_{il} - \bar{Y}(t_{il})\} (t_{il} - t_{i,l-})}$

$E(Y_i|X_i) = \hat{E}(Y_i|X_i)$

$$\{\hat{ik}, Y_i\} \quad \{\hat{ik}, \hat{\xi}_{im}\} \quad i = 1, \dots, n,$$

$$K(n) \rightarrow \infty, \quad M = M(n) \rightarrow \infty, \quad n \rightarrow \infty$$

$$\hat{f}_{mk}(x) = \hat{\beta}(x) \quad M(1)$$

Theorem 1. $\hat{E}(Y|X) - E(Y|X) \xrightarrow{p} 0$

$$\hat{f}_k(x) - f_k(x) \xrightarrow{p} 0, \quad (11)$$

$$\hat{f}_{km}(x) - f_{km}(x) \xrightarrow{p} 0, \quad (12)$$

$$|\hat{f}_k(x) - f_k(x)| = \tilde{\vartheta}_{mk}(x) = |\hat{f}_{mk}(x) - f_{mk}(x)|$$

Theorem 2. $\hat{E}(Y|X) - E(Y|X) \xrightarrow{p} 0$

$$\hat{E}(Y|X) - E(Y|X) \xrightarrow{p} 0, \quad (13)$$

$$\hat{E}(Y|X) = \bar{Y} + \sum_{k=1}^K \hat{f}_k(x)$$

$$\hat{E}\{Y(t)|X\} - E\{Y(t)|X\} \xrightarrow{p} 0, \quad (14)$$

$$\hat{E}\{Y(t)|X\} = \hat{Y}(t) + \sum_{k=1}^K \sum_{m=1}^M \hat{f}_{mk}(x) \hat{m}(t)$$

$$|\hat{E}(Y|X) - E(Y|X)| = \vartheta_n^* = |\hat{E}(Y(t)|X) - E(Y(t)|X)|$$

6. A

$M(1)$

$n =$

$X_i = X(s) = s + (s) \leq s \leq$

$(s) = - (s/)/\sqrt{}$

$s \leq$

$= \dots, k = k \geq$

$\epsilon_{ij} \sim (,)$

$ik \sim \mathcal{N}(, k)$

$ik = \sqrt{k}(Z_{ik} -)/$

$Z_{ik} \sim (,)$

$k = ,$

... ..

[,]

{ , ..., }

{ , ..., }

X_i^*
 U_{ij}^* U_{ij}

(Y_i^*)

$Y_i = \sum_{k=1}^m f_k(x_{ik}) + \varepsilon_i$

X_i Y_i $\varepsilon_i \sim (,)$ $Y = X_i^* Y_i^* U_{ij}^* V_{il}^*$

$Y = M$

() $f_k(x) = x - k$ $k = ,$

() $f(x) = x$ $f(x) = x/$

$\hat{f}_k(x) = \sum_{i=1}^n (Y_i - \bar{Y})(\hat{x}_{ik} - \bar{x}_k) / \sum_{i=1}^n (Y_i - \bar{Y})^2$

$\bar{Y}_i = \sum_{i=1}^n Y_i/n$ $\bar{x}_k = \sum_{i=1}^n \hat{x}_{ik}/n$ X_i \hat{x}_{ik}

E ()

M

f_k

M ()

() M ()

	M							
	M							
	M							
	M							
	M							
	M							

E () M $n =$ M E ()

f_{km} $\hat{f}_{km}(x) = \sum_{i=1}^n (\hat{\xi}_{im} - \bar{\xi}_m)(\hat{x}_{ik} - \bar{x}_k) / \sum_{i=1}^n (\hat{\xi}_{im} - \bar{\xi}_m)^2$

$Y_i(t) = Y(t) + \zeta_i(t)$
 $Y(t) = t + (t)$ $(t) = - (t/)/\sqrt{}$ ζ_i

ζ_i $\leq t \leq$

$f_{km}, k = , m = ()$ $f_k(x) = x - k$

$\zeta_i = \sum_{k=1}^m (\hat{x}_{ik} - \bar{x}_k)$ ()
 $\zeta_i = i + i/ -$ ε_{il} ()

$N(,)$

$X_i^* Y_i^* U_{ij}^* V_{il}^*$ U_{ij} V_{il} (E)

$E_i = \frac{(Y_i^* - \hat{Y}_i^*)}{Y_i^*}$ ()

$E_{i,f} = \frac{\int (Y_i^*(t) - \hat{Y}_i^*(t)) dt}{\int Y_i^*(t) dt}$

E M

M f_k f_{km}

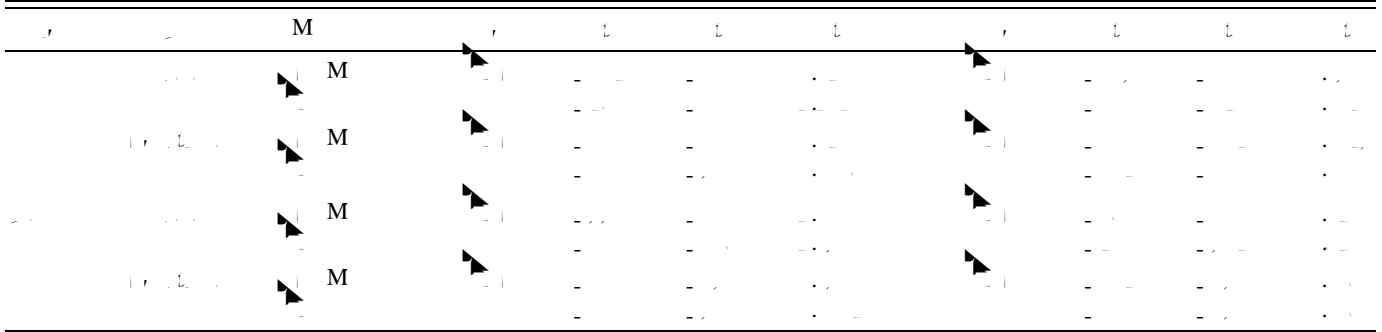
M

() M

M

M ()

() M



M

E

M

()

()

7. A A X
A A

Drosophila

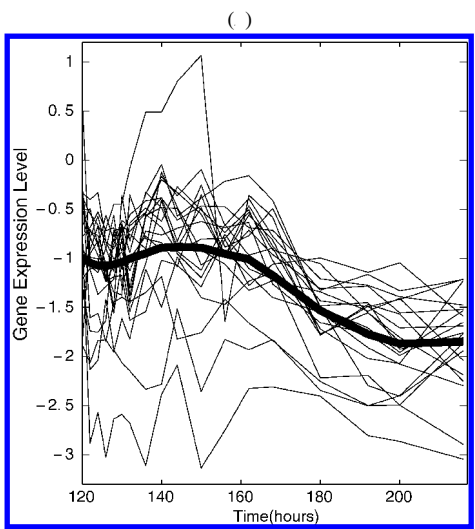
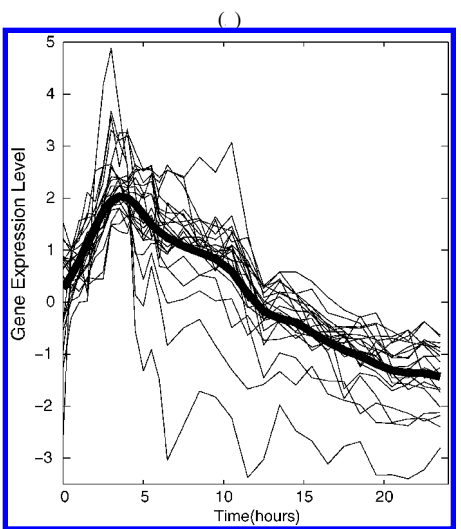
M

n =

$\hat{\xi}_i, \hat{\xi}_i, \hat{\xi}_i, \hat{\xi}_i$

()

$\hat{\xi}_i, \hat{\xi}_i$



()

()

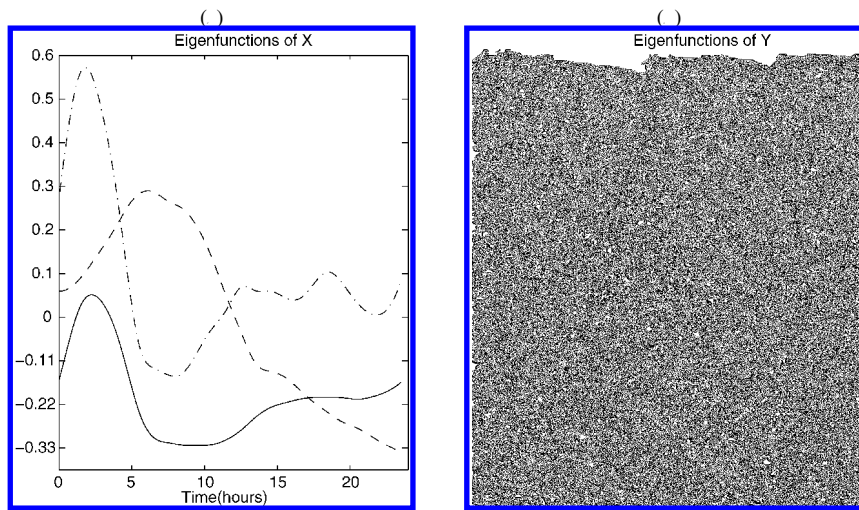


Figure 1. (a) Eigenfunctions of X (solid line), Y (dashed line), and Z (dash-dot line). $K = \dots$ (solid line), Y (dashed line), and Z (dash-dot line). $M = \dots$ (solid line), Y (dashed line), and Z (dash-dot line).

... M ... M ...

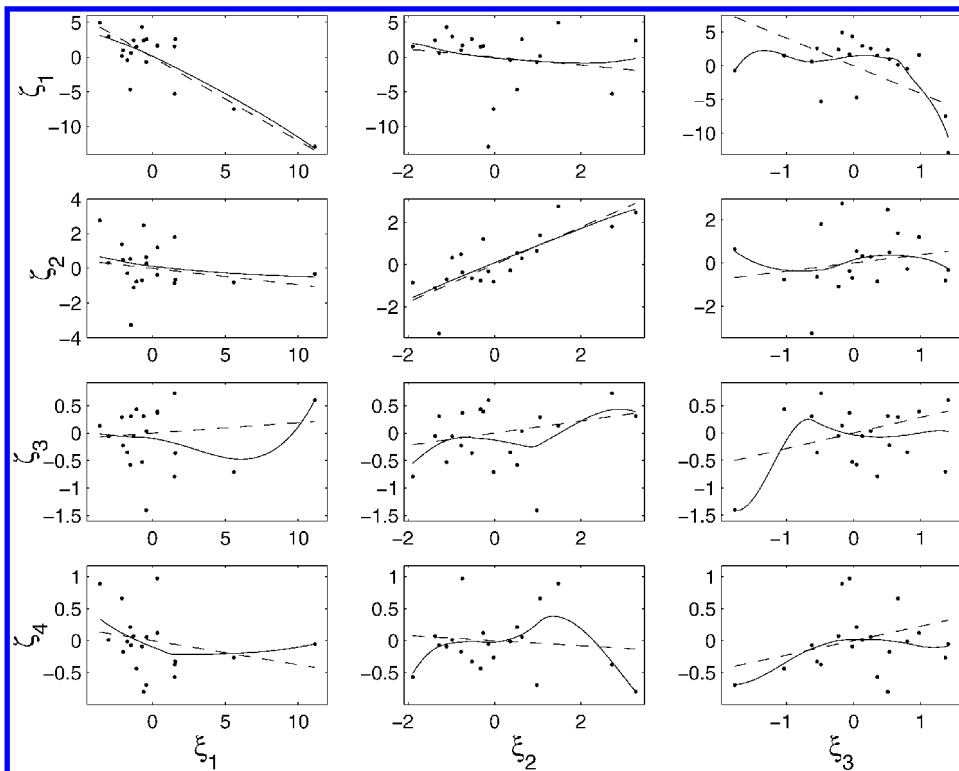


Figure 2. Scatter plots of ζ_m versus ξ_k for $m = 1, 2, 3, 4$ and $k = 1, 2, 3$. The solid line represents the fitted curve, the dashed line represents the linear regression, and the dotted line represents the linear regression.

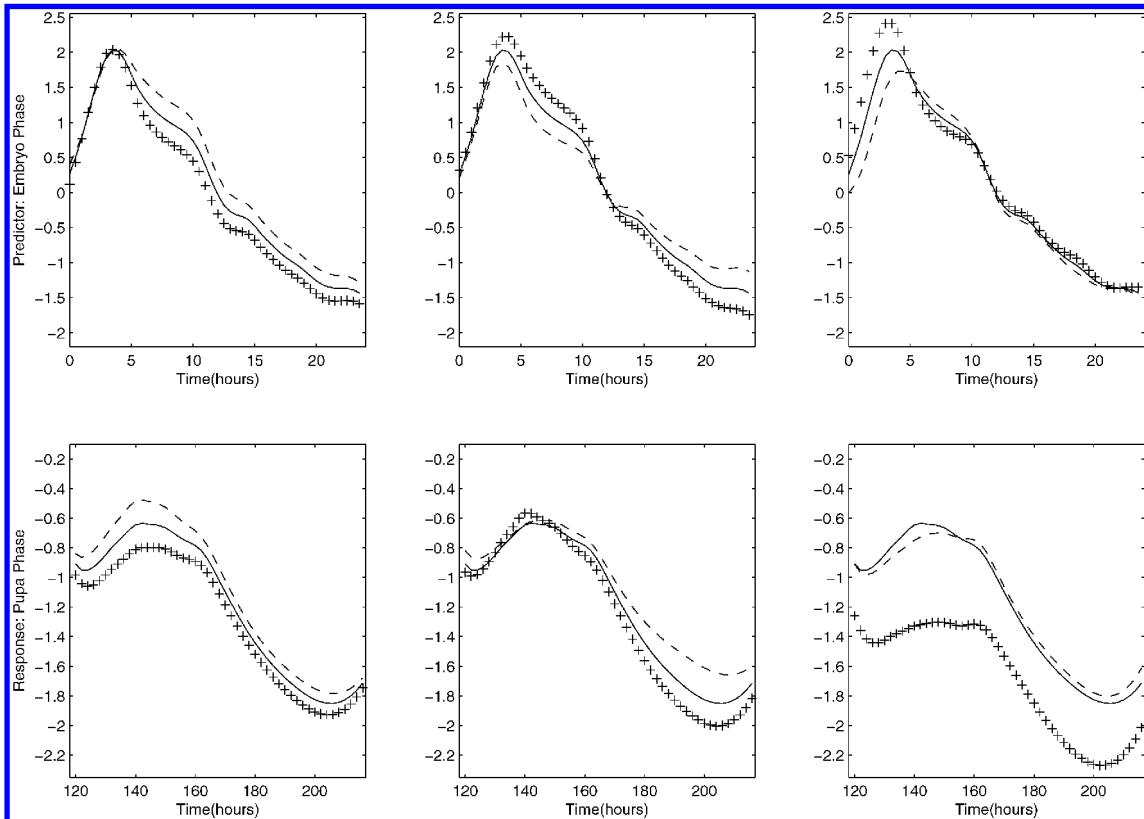
$R(\dots)$
 $E_{(-i),f(\dots)}$

	M	R
M		

$R(\dots)$
 $E_{(-i),f(\dots)}$
 M

8. A

M



$\hat{X}(s) + \alpha \hat{k}(s)$, $\alpha = (\dots)$, $\alpha = -(-)$, $\alpha = -(++)$ $k = (\dots)$ $k = (\dots)$
 $\hat{Y}(t) + \sum_{m=1}^M \{ \hat{f}_{km}(\alpha) + \sum_{\ell \neq k} \hat{f}_{\ell m}(\dots) \} \hat{m}(t)$

where $\mathbf{A} = \mathbf{A}^T \in \mathbb{R}^{n \times n}$.

Let $\mathcal{S} = [a, b]$ with $a = \min\{s : s \in \mathcal{S}\}$, $b = \max\{s : s \in \mathcal{S}\}$, $|\mathcal{S}| = b - a$, and $\mathcal{S} = [a + |\mathcal{S}|/2, b - |\mathcal{S}|/2]$. Let $\hat{X} = \hat{X}(s)$ be the solution of

$$\hat{X}' = \int \{\hat{V}_X(s) - \tilde{G}_X(s)\} ds / |\mathcal{S}| \quad (1)$$

with $\hat{X}(a) = \hat{X}(b) = \mathbf{E} \{ \mathbf{k} \mid \mathbf{k} \in \mathbb{R}^n, \mathbf{k}^T \mathbf{A} \mathbf{k} = 1 \}$. Let $\hat{X} = \{\hat{X}(k), \hat{X}(k) \mid k \geq 1\}$ be the sequence of solutions of (1) with $\hat{X}(k) = \hat{X}(k)$.

here $D_{\mathbf{Y}} = \pi_{\mathbf{k}}^{\mathbf{y}}$ and $M_{\mathbf{0}, \mathbf{k}}$ are defined analogously to (1) for process Y

Let $\|f\|_{\infty} = \int_{\mathcal{A}} |f| dt$ for any f on \mathcal{A} and $\|g\| = \sqrt{\int_{\mathcal{A}} g^2 dt}$ for any $g \in L^2(\mathcal{A})$ and define

$$\theta_{\mathbf{ik}}^{(1)} = c_1 \|X_{\mathbf{i}}\| + c_2 \|X_{\mathbf{i}} X'_{\mathbf{i}}\|_{\infty} + c_3, \quad Z_{\mathbf{k}}^{(1)} = \int_{\mathcal{S}} \mathbb{P}_{\mathbf{s} \in \mathcal{S}} |\phi_{\mathbf{k}, \mathbf{s}} - \phi_{\mathbf{k}, \mathbf{s}'}|,$$

$$\theta_{\mathbf{ik}}^{(2)} = \|\phi_{\mathbf{k}} \phi'_{\mathbf{k}}\|_{\infty}, \quad Z_{\mathbf{k}}^{(2)} = \int_{\mathcal{S}} \mathbb{P}_{\mathbf{s} \in \mathcal{S}} |\mu_{\mathbf{X}, \mathbf{s}} - \mu_{\mathbf{X}, \mathbf{s}'}|,$$

$$\theta_{\mathbf{ik}}^{(3)} = c_4 \|X_{\mathbf{i}}\|_{\infty} + c_5 \|X'_{\mathbf{i}}\|_{\infty} + c_6, \quad Z_{\mathbf{k}}^{(3)} = \|\phi'_{\mathbf{k}}\|_{\infty},$$

$$\theta_{\mathbf{ik}}^{(4)} = \left| \sum_{j=2}^{n_i} \epsilon_{ij} \phi_{\mathbf{k}, s_{ij}} - s_{ij} - s_{i, j-1} \right|, \quad Z_{\mathbf{k}}^{(4)} = \Xi,$$

$$\theta_{\mathbf{ik}}^{(5)} = \sum_{j=2}^{n_i} |\epsilon_{ij}| |s_{ij} - s_{i, j-1}|, \quad j \quad ((668084(1)428236())668 \quad 4 \ 011 \quad 0840234 \quad 008 \quad ()38)$$

Figure 4. e4_s folio 3

$$\theta_n^* = \sum_{k=1}^K \left\{ \frac{\theta_k \xi_k}{h_k} \left[-|f_k''(\xi_k)| h_k^2 \sqrt{\frac{Y|\xi_k| \|K_1\|^2}{p_k \xi_k n h_k}} \right] + \left| \sum_{k \geq K+1} f_k(\xi_k) \right| \right\}$$

$$\vartheta_n^* = \sum_{k=1}^K \sum_{m=1}^M \left\{ \frac{\theta_k \xi_k}{h_{mk}} \left[\vartheta_{mk}(\xi_k) |\psi_m(\xi_k)| \left[-|f_{mk}''(\xi_k)| \psi_m(\xi_k) h_{mk}^2 \sqrt{\frac{\zeta_m |\xi_k| \|K_1\|^2}{p_k \xi_k n h_k}} \right] \right] + \frac{\pi_m^y |f_{mk}(\xi_k)|}{\psi_m(\xi_k)} \right\}$$

Now in ξ_{ik} , η_{ik} , τ_{ik} , one finds

$$|\xi_{ik} - \eta_{ik}| \leq \{|\eta_{ik} - \xi_{ik}| + |\tau_{ik}|\}.$$

So of one side, $\|\phi_k\|_\infty \geq r$, $\|\phi'_k\|_\infty \geq r$, $\|X_i\|_\infty \geq r$ and $\|X'_i\|_\infty \geq r$. So $\theta_{ik}^{(1)}$ and $Z_k^{(1)}$, $l = 1, \dots, n$, are found on the basis of

$$\begin{aligned} & \left\{ \sum_{j=2}^{n_i} |X_i s_{ij} - \mu_{s_{ij}}| \cdot |\phi_k s_{ij} - \phi_k s_{ij}| + |\mu_{s_{ij}} - \mu_{s_{ij}}| \cdot |\phi_k s_{ij} - s_{ij} - s_{ij-1}| \right\} \\ & \leq \left\{ \sum_{j=1}^{n_i} |X_i s_{ij}| + |\mu_{s_{ij}}| r^2 |s_{ij} - s_{ij-1}| \right\}^{1/2} \left\{ \sum_{j=2}^{n_i} \phi_k s_{ij} - \phi_k s_{ij}^2 |s_{ij} - s_{ij-1}| \right\}^{1/2} \\ & \quad \left\{ \sum_{j=1}^{n_i} \mu_{s_{ij}} - \mu_{s_{ij}}^2 |s_{ij} - s_{ij-1}| \right\}^{1/2} \left\{ \sum_{j=2}^{n_i} \phi_k^2 s_{ij} |s_{ij} - s_{ij-1}| \right\}^{1/2} \\ & \leq \theta_{ik}^{(1)} Z_k^{(1)} + \theta_{ik}^{(2)} Z_k^{(2)}. \end{aligned}$$

So second side on the basis of the type of

$$|\eta_{ij} - \xi_{ik}| \leq \|X_j - \mu_{s_{ij}} \phi_k - X_j - \mu_{s_{ij}} \phi'_k\|_\infty \leq \theta_{ik}^{(3)} Z_k^{(3)}.$$

So the side, the side on the basis of $\theta_{ik}^{(4)} Z_k^{(4)} + \theta_{ik}^{(5)} Z_k^{(5)}$

□

Proof of Theorem So precisely, denote $\sum_{i=1}^n Y_i$, $w_i = K_1\{x - \xi_{ik}/h_k\}/nh_k$, $w_i = K_1\{x - \xi_{ik}/h_k\}/nh_k$, and $\theta_k = \theta_k(x)$ on the side, the side of $f_k(x)$ of the side on the side on $f_k(x)$ can be precisely expressed as

$$f_k(x) = \frac{\sum_i w_i Y_i}{\sum_i w_i} - \frac{\sum_i w_i \xi_{ik} - x}{\sum_i w_i} f'_k(x),$$

So

$$f'_k(x) = \frac{\sum_i w_i \xi_{ik} - x Y_i - \{\sum_i w_i \xi_{ik} - x \sum_i w_i Y_i\} / \sum_i w_i}{\sum_i w_i \xi_{ik} - x^2 - \{\sum_i w_i \xi_{ik} - x\}^2 / \sum_i w_i}.$$

Let $f_k(x)$ be the type of the side, so, so found by the side w_i and ξ_{ik} for w_i , ξ_{ik} and $f_k(x) - f_k(x)$, one side of the side

of the density

$$D_1 = \sum_i w_i - \hat{w}, \quad D_2 = \sum_i w_i - \hat{w} Y_i, \\ D_3 = \sum_i w_i \xi_{ik} - w_i \xi_{ik}, \quad D_4 = \sum_i w_i \xi_{ik}^2 - w_i \xi_{ik}^2.$$

Consider D_1 , the sum of the components of K_1 since K_1 is Lipschitz continuous,

$$D_1 \leq \frac{c}{nh_k^2} \sum_i |\xi_{ik} - \xi_{ik}| \{I_{|x - \xi_{ik}| \leq h_k} - I_{|x - \xi_{ik}| \leq h_k}\},$$

for $c > 0$, we have $I_{|x - \xi_{ik}| \leq h_k}$ and $I_{|x - \xi_{ik}| \leq h_k}$ are functions of x and ξ_{ik} on the set of

$$\frac{1}{nh_k^2} \sum_i |\xi_{ik} - \xi_{ik}| I_{|x - \xi_{ik}| \leq h_k} \leq \sum_{l=1}^5 Z_k^{(l)} \frac{1}{nh_k^2} \sum_i \theta_{ik}^{(l)} I_{|x - \xi_{ik}| \leq h_k}.$$

Apply the central limit theorem and the law of large numbers and Borel-Cantelli lemma, since $\sum_i I_{|x - \xi_{ik}| \leq h_k} / nh_k^2 \xrightarrow{p} p_k(x)$, one finds

$$\frac{1}{nh_k} \sum_i \theta_{ik}^{(l)} I_{|x - \xi_{ik}| \leq h_k} \xrightarrow{p} p_k(x) E \theta_{ik}^{(l)},$$

provided $E \theta_{ik}^{(l)} < \infty$ for $l = 1, \dots, 5$. Note that $E \theta_{ik}^{(1)} < \infty$, $E \theta_{ik}^{(3)} < \infty$ and $E \theta_{ik}^{(4)} \leq \sigma_X \sqrt{X^*}$ and $E \theta_{ik}^{(5)} \leq |S| \sigma_X$ by the Cauchy-Schwarz inequality when

$$Z_k^{(1)} \frac{1}{nh_k^2} \sum_i \theta_{ik}^{(1)} I_{|x - \xi_{ik}| \leq h_k} = O_p \left\{ \frac{\pi_k^x}{\sqrt{nh_X^2 h_k}} p_k(x) \right\}, \\ Z_k^{(2)} \frac{1}{nh_k^2} \sum_i \theta_{ik}^{(2)} I_{|x - \xi_{ik}| \leq h_k} = O_p \left\{ \frac{1}{\sqrt{nb_X h_k}} p_k(x) \right\}, \\ Z_k^{(3)} \frac{1}{nh_k^2} \sum_i \theta_{ik}^{(3)} I_{|x - \xi_{ik}| \leq h_k} = O_p \left\{ \frac{\|\phi_k\|_\infty^*}{h_k} p_k(x) \right\}, \\ Z_k^{(4)} \frac{1}{nh_k^2} \sum_i \theta_{ik}^{(4)} I_{|x - \xi_{ik}| \leq h_k} = O_p \left\{ \frac{\sqrt{X^*}}{h_k} p_k(x) \right\}, \\ Z_k^{(5)} \frac{1}{nh_k^2} \sum_i \theta_{ik}^{(5)} I_{|x - \xi_{ik}| \leq h_k} = O_p \left\{ \frac{\pi_k^x}{\sqrt{nh_X^2 h_k}} p_k(x) \right\}.$$

and note that $n^{-1} \sum_i |\xi_{ik} - \xi_{ik}| I_{|x - \xi_{ik}| \leq h_k} = O_p(\theta_k h_k^{-1})$ by the law of large numbers and the second order Taylor expansion of θ_k around ξ_{ik} .

$$\frac{1}{nh_k} \sum_i I_{|x - \xi_{ik}| \leq h_k} \leq \frac{1}{nh_k} \sum_i \{I_{|x - \xi_{ik}| \leq h_k} I_{\sum_{k=1}^5 \theta_{ik}^{(k)} Z_k^{(k)} > h_k}\} \xrightarrow{p} p_k(x),$$

and note that $n^{-1} \sum_i |\xi_{ik} - \xi_{ik}| I_{|x - \xi_{ik}| \leq h_k} = O_p(\theta_k h_k^{-1})$ in D_1 by the law of large numbers.

And by the law of large numbers, $D_2 = O_p(\theta_k h_k^{-1})$, apply the central limit theorem for $\theta_{ik}^{(k)}$, $l = 1, \dots, k$, and the independence between Y_i and $\theta_{ik}^{(k)}$ for $l = 1, \dots, k$ in the second order condition D_3 , one has

$$D_3 = \sum_i \{w_i - \hat{w}_i \xi_{ik} \quad w_i - \hat{w}_i \xi_{ik} - \xi_{ik} \quad w_i \xi_{ik} - \xi_{ik}\} \equiv D_{31} \quad D_{32} \quad D_{33}.$$

In $D_{31} = O_p(\theta_k h_k^{-1})$, by the law of large numbers, $D_{32} = O_p(D_{31})$ since $D_{33} \leq c \sum_{k=1}^5 Z_k^{(k)} n^{-1} \sum_i \theta_{ik}^{(k)} I_{|x - \xi_{ik}| \leq h_k}$ for some $c > 0$, one has $D_{33} = O_p(D_{31})$ by the law of large numbers in $D_3 = O_p(\theta_k h_k^{-1})$. One has $|\xi_{ik}^2 - \xi_{ik}^2| \leq |\xi_{ik} - \xi_{ik}| \cdot |\xi_{ik} + \xi_{ik}| \leq \xi_{ik}^2$, one can use $D_4 = O_p(\theta_k h_k^{-1})$ in D_3 and $E\xi_{ik}^4 < \infty$ for the central limit theorem for D , $l = 1, \dots, k$, and apply the law of large numbers to $|f_k(x) - f_k(x)| = O_p(\theta_k h_k^{-1})$ in A , and apply the law of large numbers for the Taylor expansion of $f_k(x)$ to prove the proof of D_3 .

Therefore, it only needs to consider $\sum_i w_i \zeta_{im} - w_i \zeta_{im} = \sum_i \{w_i - \hat{w}_i \zeta_{im} \quad w_i - \hat{w}_i \zeta_{im} - \zeta_{im} \quad w_i \zeta_{im} - \zeta_{im}\}$, where the second order condition of $O_p(\vartheta_{mk}^{-1})$ holds.

$$\left| \sum_i w_i \zeta_{im} - \zeta_{im} \right| \leq \sum_{m=1}^5 Q_m^{(k)} \sum_i w_i \vartheta_{im}^{(k)} \leq \frac{1}{nh_{mk}} \sum_{m=1}^5 Q_m^{(k)} \sum_i \vartheta_{im}^{(k)} I_{|x - \xi_{ik}| \leq h_{mk}}$$

It follows that the proof is complete. \square

Proof of Theorem 3.1. In A , the definition of θ_n^* in (3.1) holds,

for non zero ϵ in \mathcal{S} or $\epsilon = 0$, no ϵ

$$\begin{aligned}
 & \widehat{E}\{Y^\epsilon | X\} - E\{Y^\epsilon | X\} \\
 & \leq \sum_{k=1}^K \sum_{m=1}^M |f_{mk}(\xi_k) \psi_m^\epsilon - f_{mk}(\xi_k) \psi_m| + \sum_{k \geq K+1} \sum_{m \geq M+1} |f_{mk}(\xi_k) \psi_m^\epsilon| \\
 & \leq \sum_{k=1}^K \sum_{m=1}^M |f_{mk}(\xi_k) - f_{mk}(\xi_k)| \{|\psi_m^\epsilon| + |\psi_m^\epsilon - \psi_m|\} + |f_{mk}(\xi_k)| \cdot |\psi_m^\epsilon - \psi_m| \\
 & \quad + \left| \sum_{(k,m) \in \mathcal{N}^2 \setminus \mathcal{N}_K \times \mathcal{N}_M} f_{mk}(\xi_k) \psi_m^\epsilon \right|.
 \end{aligned}$$

\mathcal{S} is piecewise constant ϵ and ϵ_n^* in \mathcal{S}