where

$$D = \begin{bmatrix} \int M(x)dx & 0 \\ 0 & \operatorname{diag}\left\{ \int \begin{bmatrix} M & M_j \\ M_j & M_{jj} \end{bmatrix} dx \right\}_{j=1,\ldots,d} \end{bmatrix}, \quad A = \begin{bmatrix} 1 & 0^\top \\ 0 & \Pi \end{bmatrix}.$$

Since $g'(\theta_K(\cdot))V(\theta_K(\cdot))$ is bounded and $\mu_K(\cdot)$ is bounded away from 0, one can obtain that D is bounded. Using the same technique, we can prove that Π is one-to-one and onto, and $\|\Pi\| \le d\|K\|$. Hence Π has a bounded inverse, which implies that A also has, i.e. there exists a constant c such that $\|\Psi_K(\beta_K^* + c)\| \le c$.

The other conditions are verified as follows. To prove that Ψ_K satisfies the Lipschitz condition $\|\Psi_K - \Psi_K'\| \le c\|\beta_K - \beta_K'\|$, by the decomposition (2), it is sufficient to prove the boundedness of D and A, which is guaranteed by the smoothness and boundedness of $g'(\theta_K(\cdot))V(\theta_K(\cdot))$ and $\mu_K(\cdot)$. Finally, by the uniform continuity of Ψ_K and the fact $\Psi_K(\beta_K^*) = 0$, there exists a positive constant r such that $\sup_{\beta \in B_r(\beta_K^*)} \|\Psi_K(\beta)\| < (2c^2)^{-1}$. This proves that if $\beta_K^* + c \in B_r(\beta_K^*)$, then $\|\{\beta - \Psi_K(\beta_K^* + c)\} - \Psi_K(\beta_K^* + c)\| < (2c^2)^{-1}$. Note that M is close to $\overline{Q}_K$, the two norms $\|\cdot\|_M$ and $\|\cdot\|_{\overline{Q}_K}$ are equivalent. Conclusion (1) now follows from Lemma 1. Theorem 1 (2) follows from the property of Hilbert-Schmidt operators Π_j; see Theorem 4.B in Appendix 4 of Bickel et al. (1993) and Theorem 4 of Yu et al. (2008) for details. □

S.3.2 Proof of Lemma 2-3

We first prove Lemma 2. Recall that Δ is defined in (23). The proof is based on the decomposition of Δ.

Proof. We further decompose $_j(x_j) = \ ^A_j(x_j) + \ ^B_j(x_j)$; $\ _j(x_j) = \ ^A_j(x_j) + \ ^B_j(x_j)$ that

$$\begin{bmatrix} \ ^A_j(x_j) \\ \ ^A_j(x_j) \end{bmatrix} = \begin{bmatrix} \ _j(x_j) \\ \ _j(x_j) \end{bmatrix} - \begin{bmatrix} E(\ _j(x_j) \mid X\ ; : : : ; X_K) \\ E(\ _j(x_j) \mid X\ ; : : : ; X_K) \end{bmatrix};$$

$$\begin{bmatrix} \ ^B_j(x_j) \\ \ ^B_j(x_j) \end{bmatrix} = \begin{bmatrix} E(\ _j(x_j) \mid X\ ; : : : ; X_K) \\ E(\ _j(x_j) \mid X\ ; : : : ; X_K) \end{bmatrix}:$$

We omit the constants in the functions and de ne the spaces

$$\overline{H}\ (Q) = \ f = (f\ (x\ ); : : : ; f_d(x_d); f\ \ (x\ ); f\ _d(x_d))^> :$$

$$\int (Q\ \ f_j + Q\ _j f\ _j)dx = 0 \text{ for } j = 1; : : : ; d\ \ ;$$

$$\overline{H}_j(Q) = \{f\ f\ 2\ \overline{H}\ (Q) : f \text{ depends only on } x_j\}:$$

In this proof, we consider $2d$-dimensional functions. Let $\ _j$ be the projection operator from $\overline{H}\ (Q_K)$ onto $\overline{H}_j(Q_K)$. Then for any $\ \ 2\ \overline{H}\ (Q_K)$,

$$_j\ _\ell(x_\ell) = f_\ell(x_\ell); \qquad _j\ \ _\ell(x_\ell) = f\ _\ell(x_\ell);$$

where for $\ell \neq j$, $f_\ell(x_\ell) = \ _\ell(x_\ell)$ and $f\ _\ell(x_\ell) = \ \ _\ell(x_\ell)$, and

$$f_j(x_j) = g_j(x_j) - \int g_j(x_j)\overline{Q}_{K,\ }(x)dx;$$

$$\begin{bmatrix} g_j(x_j) \\ f\ _j(x_j) \end{bmatrix} = \sum_{\ell \neq j} \left(\int \begin{bmatrix} \overline{Q}_{K,\ } \\ \overline{Q}_{K,j} \end{bmatrix} \begin{bmatrix} \overline{Q}_{K,\ _j} & \overline{Q}_{K,\ \ell} \\ \overline{Q}_{K,jj} & \overline{Q}_{K,j\ell} \end{bmatrix} dx\ _j \right) \int \begin{bmatrix} \overline{Q}_{K,\ } \\ \overline{Q}_{K,j} \end{bmatrix} \begin{bmatrix} \ _\ell(x_\ell) \\ \ _\ell(x_\ell) \end{bmatrix} dx\ _j:$$

Then de ne $T = \ _d$. Recall that $!_{ki}(x;\ )$ plays the same role of $K_h(X_{ki} \ \ x)$ in Mammen (1999). With assumption (A2) on the smoothness of link function g, conclusions of AM can be carried over to GAM and we can obtain that T is smaller than $\ < 1$ w.p.1. Let $_j(x_j) = \int \sum_k^K P_{k,\ }(\ \ ; e_{kjK})dx\ _j$, $\ _j(x_j) = \int \sum_k^K P_{k,j}(\ \ ; e_{kjK})dx\ _j$, $_{,j}(x_j) = \int \overline{Q}_{K,\ }(x)dx\ _j$ and $_{,\ j} = \int \overline{Q}_{K,\ _j}(x)dx\ _j$. Then we have the following expression for $\ , \ = T\ + \ $, where $\ = \ + \ $. By iterative applications, we have

$^{s} = \sum_{i}^{1} T^{i}\ ^{s}$ for $s = A; B$. Based on these stochastic expansions, one can use the techniques in the proof of Theorem 1{2 in Mammen and Nielsen (1999) to obtain the following result: for x_j 2 (0; 1),

$$\sup\ {}_{j}^{A}(x_j) \qquad {}_{j}(x_j) \qquad = o_p(N_K^{\ /}\ );$$

$$\sup\ {}_{j}^{B}(x_j) \quad b_j(x_j) \ = o_p(N_K^{\ /}\ );$$

and the asymptotic distribution of follows from the standard theory of kernel smoothing.

□

Now we present the proof of Lemma 3, which is a product of the pre-speci ed bandwidth order in Assumption (A5).

Proof. Noting that F_K di ers from $\hat{F}_K$ only in the bandwidths, the proof of Lemma 6 of Yu et al. (2008) can be carried over by substituting ${}_{Kj,i}$ for h_j^i. By Assumption (A5), we have

$$kF_K\ {}_K k_{p,} = o_p\ N_K^{\ /}\ ; \quad kF_K\ {}_K k_1 = o_p\ N_K^{\ /}\ :$$

We note that $\tilde{F}_K$ is the linear approximation of F_K, then $kF_K\ {}_K k\ '\ k\tilde{F}_K\ {}_K k$ for norms $k\ k_{p,}$ and $k\ k_1$, which gives

$$k\tilde{F}_K\ {}_K k_{p,} = o_p\ N_K^{\ /}\ ; \quad k\tilde{F}_K\ {}_K k_1 = o_p\ N_K^{\ /}\ : \tag{3}$$

Finally, we can use the same techniques in proof of Theorem 1 by substituting ${}_K$ for e_K^{bmc} to prove that the su cient conditions of Lemma 1 hold when setting = ${}_K$. This implies that ${}_K$ must be close to e_K at the same rate as (3), which complete the proof. □

S.3.3 Proof of Proposition 1

Proof. Using the same technique in the proof of Theorem 2, we can derive that

$$Ef(e_{Kj} \qquad {}_j)\ g = A\ {}_j\ {}_{Kj,}^{\theta} + A\ {}_j N_K\ {}_{Kj,}^{\theta} \qquad + A\ {}_j N_K\ {}_{Kj,}^{\theta}$$

$$+ o_p \quad {}^{\theta}_{Kj,} + N_K \quad {}^{\theta}_{Kj,} \quad + N_K \quad {}^{\theta}_{Kj,} \quad ;$$

where $A_{\ j}; A_{\ j}; A_{\ j}$ are constants and

$${}^{\theta}_{Kj,i} = \frac{1}{N_K} \sum_k n_k (\hat{e}^{\theta}_{kjK,j})^i; \ i = 2; \quad 5; \quad 9:$$

Using the same argument as S.3.4, when (21) and (22) hold, the online estimates $\hat{e}_{Kj}$ satisfies $\hat{e}_{Kj} \quad {}_j = O_p\ N_K{}^{/}$. Substituting the expression of $\hat{\theta}_{Kj}$ in (16) and h_{Kj} in (14), we obtain

$$\frac{\hat{\theta}_{Kj} \quad h_{Kj}}{h_{Kj}} = \frac{1}{5} \quad \frac{{}_j}{\hat{e}_{Kj}} \quad ! \ {}^{\frac{1}{5}} \quad \frac{\hat{e}_{K,j} \quad {}_j}{{}_j} \qquad \frac{1}{5} \frac{\hat{e}_{Kj} \quad {}_j}{{}_j}:$$

When $h^{\sigma}_{Kj} = O_p(N_K{}^{/})$, $\hat{e}_{Kj}(u) \quad {}_j(u) = O_p(N_K{}^{/})$ and then $\hat{e}_{K,j} \quad {}_j = O_p(N_K{}^{/})$, and hence the convergence rate of $\hat{\theta}_{Kj}$ is dominated by $\hat{e}_{Kj} \quad {}_j$. □

S.3.4 Proof of Theorem 3

Proof. This result follows directly from Theorem 4 in Yang and Yao (2022) based on the oracle properties of the proposed estimate in Theorem 2. The optimal bandwidth h_{Kj} as in (14) is strictly decreasing with K. Thus the candidate sequence shall be decreasing with ${}_{kj} = \hat{\theta}_{kj}$. There is no efficiency loss if $\hat{e}_{kjK,j} = \hat{h}_{Kj}$ which implies that the optimal ${}_{lj}$ shall make $\hat{e}_{kjK,j}$ as close to $\hat{h}_{Kj}$ as possible. With the convergence of $\hat{\theta}_{kj}$, we have

$$\frac{\hat{e}_{kjK,j}}{\hat{h}_{Kj}} = g(l) \quad \frac{N_k}{N_K} \quad {}^{\frac{1}{5}} + O_p \quad N_k{}^{\frac{2}{7}} \quad :$$

Write $g(l) = fg(l)\ {}^{/\lambda} g^{\lambda}$ and note that N_k/N_K grows linearly, then shall be 1/5 and the optimal $g(l)\ {}^{/\lambda}$ shall be linear between $(0; 1)$. Hence, the optimal is

$${}_{Kj\ell} = \quad \frac{L \quad \grave{} + 1}{L} \quad {}^{\frac{1}{5}} \hat{\theta}_{Kj}:$$

Next we derive the asymptotic lower bound for the relative e ciency. Writing $\hat{h}_{Kj}$ = $h_{Kj}f1 + O_p(N_K^{\ /})g$ and using the expressions of h_{Kj} as in (14), one can derive

$eff(e_{Kj})$

$$+\frac{4}{5}\left(\frac{5}{6}\right)^{\frac{1}{5}} L^{\frac{1}{5}} \quad {}^{\frac{1}{5}}+1 \qquad +O_p\left(\frac{N_K{}^{\frac{1}{5}}}{L}+N_K{}^{\frac{2}{7}}\right)^{!}: \tag{5}$$

The property of breakpoint K also guarantee that

$$\frac{1}{L}\sum_{k}^{\frac{1}{5}\,K_0}\frac{n_k}{N_{K_0}}\theta_{kj} \quad \theta_{Kj};$$

holds with probability 1 when K tends large, which is equivalent to

$$\frac{1}{L}\sum_{k}^{\frac{1}{5}\,K_0}\left(\frac{n_k}{N_{K_0}}\left(\frac{c_k N_k{}^{\frac{1}{5}}}{c_K N_K{}^{\frac{1}{5}}}\right)\right) \quad 1:$$

Under Assumption (A6), we obtain

$$\frac{N_{K_0}}{N_K} \quad \frac{5}{4} \quad \frac{1}{L}+O_p(N_K{}^{\frac{2}{7}});$$

i.e. 2 [0; (5=4) =L] holds with probability 1 when K tends large. Note that (5) is strictly increasing with respect to on this domain. Hence we have

$$eff(\theta_{Kj}) \quad 1+c\,L \quad +c\,L \quad ;$$

where

$$c \;=\; 5\;=(3 \quad 2\;)+5\;=(6 \quad 4\;) \quad 6=5 \quad (5=4) \quad 0{:}183$$

and

$$c \;=\; f5\;=(6 \quad 4\;) \quad (5=4)\;g\;=5 \quad 0{:}0032{:}$$

This completes the proof of Theorem 3. □

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