Supplementary File for the Manuscript Titled "Semiparametric Mixture of Binomial Regression " by J. Cao and W. Yao

Proofs

Let $g(t)$ be the density function for t. The following technical conditions are imposed in this section. They are not the weakest possible conditions, but they are imposed to facilitate the proofs.

Technical Conditions:

A $\pi_1(t)$ and $p(t)$ has continuous second derivative at t_0 and $0 < \pi_1(t_0) < 1$ and $0 < p(t_0) < 1$. (For the constant proportion semiparametric mixture model (3), we use the same assumption for $p(t)$ and assume $0 < \pi_1 < 1$.)

B $g(t)$ has continuous second derivative at the point t_0 and $g(t_0) > 0$.

C $K(\cdot)$ is a symmetric (about 0) kernel density with compact support $[-1, 1]$.

D The bandwidth h tends to zero such that $nh \to \infty$.

Let $\alpha_n = (nh)^{-1/2} + h^2, \boldsymbol{\theta}_0 = \{\pi_1(t_0), p(t_0)\}$,

$$f(x, \boldsymbol{\theta}) = \pi_1 I(x = 0) + \pi_2 \binom{N}{x} p^x \{1 - p\}^{N-x},$$

$l(x, \boldsymbol{\theta}) = \log f(x, \boldsymbol{\theta})$, where $\boldsymbol{\theta} = (\pi_1, p)$. Then the objective function (4) can be written as

$$\ell(\boldsymbol{\theta}) = \frac{1}{n} \sum_{i=1}^{n} K_h(t_i - t_0) \log f(x_i, \boldsymbol{\theta}) = \frac{1}{n} \sum_{i=1}^{n} K_h(t_i - t_0) l(x, \boldsymbol{\theta}).$$

Define

$$l_1(x, \boldsymbol{\theta}) = \frac{\partial}{\partial \boldsymbol{\theta}} l(x, \boldsymbol{\theta}) \text{ and } l_2(x, \boldsymbol{\theta}) = \frac{\partial^2}{\partial \boldsymbol{\theta} \partial \boldsymbol{\theta}^T} l(x, \boldsymbol{\theta}),$$

$G(t) = \mathrm{E}\{l_1(X, \boldsymbol{\theta}_0) \mid t\}$ and $\mathcal{I}(t) = -\mathrm{E}\{l_2(X, \boldsymbol{\theta}_0) \mid t\}$. The moments of K and K^2 are denoted respectively by

$$\mu_j = \int t^j K(t)dt \qquad \text{and} \qquad \nu_j = \int t^j K^2(t)dt.$$

By some simple calculations, we can get the following results.

Lemma 1. Assume that the regularity conditions A–C hold. We have the following results

1. The $G(t)$ has continuous second derivative at t_0 and $\mathrm{E}\{l_1(X, \boldsymbol{\theta}_0)^2 \mid t\}$ is continuous at t_0.
2. The $\partial^3 \ell(\boldsymbol{\theta}_0)/(\partial\boldsymbol{\theta}_i \partial\boldsymbol{\theta}_j \partial\boldsymbol{\theta}_k)$ is a bounded function for all $\boldsymbol{\theta}$ in a neighborhood of $\boldsymbol{\theta}_0$ and all x.
3. $\mathcal{I}(t)$ is continuous at t_0 and positive definite at t_0 and

$$\mathcal{I}(t_0) = \mathrm{E}\{l_1(X, \boldsymbol{\theta}_0) l_1(X, \boldsymbol{\theta}_0)^T \mid t_0\}.$$

Proof of Theorem 2.1.
Note that

$$\ell(\boldsymbol{\theta}) = \frac{1}{n} \sum_{i=1}^{n} K_h(t_i - t_0) \log f(x_i, \boldsymbol{\theta}).$$

Hence,

$$\begin{aligned}
\ell(\boldsymbol{\theta}^{(k+1)}) - \ell(\boldsymbol{\theta}^{(k)}) &= \sum_{i=1}^{n} \log \left\{ \frac{f(x_i, \boldsymbol{\theta}^{(k+1)})}{f(x_i, \boldsymbol{\theta}^{(k)})} \right\} K_h(t_i - t_0) \\
&= \sum_{i=1}^{n} \log \left\{ \frac{\pi_1^{(k)} B(x_i, N, 0)}{f(x_i, \boldsymbol{\theta}^{(k)})} \frac{\pi_1^{(k+1)} B(x_i, N, 0)}{\pi_1^{(k)} B(x_i, N, 0)} \right. \\
&\quad \left. + \frac{\pi_2^{(k)} B(x_i, N, p^{(k)})}{f(x_i, \boldsymbol{\theta}^{(k)})} \frac{\pi_2^{(k+1)} B(x_i, N, p^{(k+1)})}{\pi_2^{(k)} B(x_i, N, p^{(k)})} \right\} K_h(x_i - x_0) \\
&= \sum_{i=1}^{n} \log \left\{ r_{i1}^{(k+1)} \frac{\pi_1^{(k+1)} B(x_i, N, 0)}{\pi_1^{(k)} B(x_i, N, 0)} + r_{i2}^{(k+1)} \frac{\pi_2^{(k+1)} B(x_i, N, p^{(k+1)})}{\pi_2^{(k)} B(x_i, N, p^{(k)})} \right\} K_h(x_i - x_0)
\end{aligned}$$

Based on the Jensen's inequality, we have

$$\begin{aligned}
\ell(\boldsymbol{\theta}^{(k+1)}) - \ell(\boldsymbol{\theta}^{(k)}) \geq \sum_{i=1}^{n} \Bigg[& r_{i1}^{(k+1)} \log \left\{ \frac{\pi_1^{(k+1)} B(x_i, N, 0)}{\pi_1^{(k)} B(x_i, N, 0)} \right\} K_h(x_i - x_0) \\
& + r_{i2}^{(k+1)} \log \left\{ \frac{\pi_2^{(k+1)} B(x_i, N, p^{(k+1)})}{\pi_2^{(k)} B(x_i, N, p^{(k)})} \right\} K_h(x_i - x_0) \Bigg]
\end{aligned}$$

Based on the property of M-step of (5), we have

$$\ell(\boldsymbol{\theta}^{(k+1)}) - \ell(\boldsymbol{\theta}^{(k)}) \geq 0.$$

Proof of Theorem 3.1. Denote $\alpha_n = (nh)^{-1/2} + h^2$. It is sufficient to show that for any given $\eta > 0$, there exists a large constant c such that

$$P\{\sup_{|u\|=c} \ell(\boldsymbol{\theta}_0 + \alpha_n u) < \ell(\boldsymbol{\theta}_0)\} \geq 1 - \eta, \tag{13}$$

where $\ell(\boldsymbol{\theta})$ is defined in (4).

By using Taylor expansion, it follows that

$$\begin{aligned}
\ell(\boldsymbol{\theta}_0 + \alpha_n u) - \ell(\boldsymbol{\theta}_0) &= \frac{1}{n}\sum_{i=1}^{n} K_h(t_i - t_0)\left\{l(x_i, \boldsymbol{\theta}_0 + \alpha_n u) - l(x_i, \boldsymbol{\theta}_0)\right\} \\
&= \frac{1}{n}\sum_{i=1}^{n} K_h(t_i - t_0)\left\{l_1(x_i, \boldsymbol{\theta}_0)^T u\alpha_n + u^T l_2(x_i, \boldsymbol{\theta}_0)u\alpha_n^2 + \alpha_n^3 q(x_i, \tilde{\boldsymbol{\theta}})\right\} \\
&= I_1 + I_2 + I_3,
\end{aligned}$$

where $\|\tilde{\boldsymbol{\theta}} - \boldsymbol{\theta}_0\| \leq c\alpha_n$ and

$$q(x_i, \tilde{\boldsymbol{\theta}}) = \sum_{i=1}^{2}\sum_{j=1}^{2}\sum_{k=1}^{2} \frac{\partial^3 l(x_i, \tilde{\boldsymbol{\theta}})}{\partial\boldsymbol{\theta}_i \partial\boldsymbol{\theta}_j \partial\boldsymbol{\theta}_k} u_i u_j u_k,$$

where $u = (u_1, u_2)$.

By directly calculating the mean and variance and note that $G(t_0) = 0$, we obtain

$$\begin{aligned}
\mathrm{E}(I_1) &= \alpha_n \mathrm{E}\left\{K_h(t - t_0)G(t)^T u\right\} = O(c\alpha_n h^2); \\
\mathtt{var}(I_1) &= n^{-1}\alpha_n^2 \mathtt{var}[K_h(t_i - t_0) l_1(\boldsymbol{\theta}_0, x_i)^T u] = O(c^2\alpha_n^2 (nh)^{-1}).
\end{aligned}$$

Hence

$$I_1 = O(c\alpha_n h^2) + \alpha_n c O_p((nh_1)^{-1/2}) = O_p(c\alpha_n^2).$$

Similarly,

$$I_3 = \frac{1}{n}\sum_{i=1}^{n} K_h(t_i - t_0)\alpha_n^3 q(x_i, \tilde{\boldsymbol{\theta}}) = O_p(\alpha_n^3).$$

and

$$I_2 = \frac{1}{n}\sum_{i=1}^{n} K_h(t_i - t_0) u^T l_2(x_i, \boldsymbol{\theta}_0) u\alpha_n^2 = -\alpha_n^2 g(t_0) u^T \mathcal{I}(t_0) u(1 + o_p(1)).$$

Noticing that $\mathcal{I}(t_0)$ is a positive matrix, $\|u\| = c$, we can choose c large enough such that I_2 dominates both I_1 and I_3 with probability at least $1 - \eta$. Thus (13) holds. Hence with probability approaching 1 (wpa1), there exists a local maximizer $\hat{\boldsymbol{\theta}}$ such that $||\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0|| \leq \alpha_n c$, where $\alpha_n = (nh)^{-1/2} + h^2$. Based on the definition of $\boldsymbol{\theta}$, we can also get, wpa1, $|\hat{\pi}(t_0) - \pi(t_0)| = O_p\left((nh)^{-1/2} + h^2\right)$ and $|\hat{p}(t_0) - p(t_0)| = O_p\left((nh)^{-1/2} + h^2\right)$.

Proof of Theorem 3.2.
Note that the estimate $\hat{\boldsymbol{\theta}}$ satisfies the equation

$$0 = \ell'(\hat{\boldsymbol{\theta}}) = \frac{1}{n}\sum_{i=1}^{n} K_h(t_i - t_0)\left\{l_1(x_i, \boldsymbol{\theta}_0) + l_2(x_i, \boldsymbol{\theta}_0)(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0) + O_p(||\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0||^2)\right\} \ . \quad (14)$$

The order of the third term could be derived from the (2) of Lemma 1. Let

$$\begin{aligned} W_n &= \frac{1}{n}\sum_{i=1}^{n} K_h(t_i - t_0) l_1(x_i, \boldsymbol{\theta}_0) \\ \Delta_n &= -\frac{1}{n}\sum_{i=1}^{n} K_h(t_i - t_0) l_2(x_i, \boldsymbol{\theta}_0). \end{aligned}$$

Note that

$$\begin{aligned} \mathrm{E}(W_n) &= \mathrm{E}\{K_h(t - t_0)G(t)\} = \frac{1}{2}(Gg)''(t_0)\mu_2 h^2(1 + o(1)), \\ \mathtt{cov}(W_n) &= n^{-1}\mathtt{cov}\{K_h(t_i - t_0) l_1(x_i, \boldsymbol{\theta}_0)\} \\ &= n^{-1}\left\{\mathrm{E}K_h^2(t_i - t_0) l_1(x_i, \boldsymbol{\theta}_0) l_1(x_i, \boldsymbol{\theta}_0)^T - \mathrm{E}(W_n)^2\right\} \\ &= (nh)^{-1} g(t_0)\mathcal{I}(t_0)\nu_0(1 + o(1)), \end{aligned} \quad (15)$$

where $(Gg)''(t)$ is the second derivative of $G(t)g(t)$, and

$$\begin{aligned} \mathrm{E}(\Delta_n) &= \mathrm{E}\{K_h(t - t_0)\mathcal{I}(t)\} = \mathcal{I}(t_0)g(t_0) + o(1), \\ \mathtt{var}(\Delta_n(i,j)) &\leq n^{-1}\mathrm{E}\left[K_h^2(t_i - t_0)\left\{\frac{\partial^2 l(x_i, \boldsymbol{\theta}_0)}{\partial\boldsymbol{\theta}_i \partial\boldsymbol{\theta}_j}\right\}^2\right] \\ &= O\{(nh)^{-1}\} = o(1). \end{aligned}$$

Therefore, we have

$$\Delta_n = \mathcal{I}(t_0)g(t_0) + o_p(1).$$

Note that $||\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0||^2 = o_p(W_n)$. Then from (14), we have

$$\sqrt{nh}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0) = g(t_0)^{-1}\mathcal{I}(t_0)^{-1}\sqrt{nh}W_n(1 + o_p(1)). \quad (16)$$

In order to prove the asymptotic normality of (16), we only need to establish the asymptotic normality of $\sqrt{nh}W_n$. Next we show, for any unit vector $d \in \Re^2$, we prove

$$\{d^T \mathtt{cov}(W_n^*) d\}^{-\frac{1}{2}}\{d^T W_n^* - d^T E(W_n^*)\} \xrightarrow{L} N(0,1),$$

where $W_n^* = \sqrt{nh}W_n$. Let

$$\xi_i = \sqrt{h/n}K_h(t_i - t_0) d^T l_1(\boldsymbol{\theta}_0, x_i).$$

Then $d^T W_n^* = \sum_{i=1}^n \xi_i$. We check the Lyapunov's condition. Based on (15), we can get $\texttt{cov}(W_n^*) = g(t_0)\mathcal{I}(t_0)\nu_0(1+o(1))$ and $\texttt{var}(d^T W_n^* d) = d^T \texttt{cov}(W_n^*) d = g(t_0)\nu_0 d^T \mathcal{I}(t_0) d(1+o(1))$. So we only need to prove $nE|\xi_1|^3 \to 0$. Noticing that $l_1(\boldsymbol{\theta}_0, x)$ is bounded for any x, and $K(\cdot)$ has compact support,

$$\begin{aligned} nE|\xi_1|^3 &\le O(nn^{-3/2}h^{3/2})E\left|K_h^3(t_i - t_0)\right| \\ &= O(n^{-1/2}h^{3/2})O(h^{-2}) = O((nh)^{-1/2}) \to 0. \end{aligned}$$

So the asymptotic normality for W_n^* holds such that

$$\sqrt{nh}\left\{W_n - \frac{1}{2}(Gg)''(t_0)\mu_2 h^2 + o(h^2)\right\} \xrightarrow{D} N\left\{0, g(t_0)\mathcal{I}(t_0)\nu_0\right\}.$$

Based on (16) and the Slutsky theorem, we can get the asymptotic result of $\hat{\boldsymbol{\theta}}$

$$\sqrt{nh}\left\{\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0 - b(t_0)h^2 + o(h^2)\right\} \xrightarrow{D} N\left\{0, g^{-1}(t_0)\mathcal{I}^{-1}(t_0)\nu_0\right\},$$

where

$$b(t_0) = \mathcal{I}^{-1}(t_0)\left\{\frac{G'(t_0)g'(t_0)}{g(t_0)} + \frac{1}{2}G''(t_0)\right\}\mu_2.$$

Proof of Theorem 3.3.
Let

$$f(x_i, \pi_1, \hat{p}(t_i)) = \log\left[\pi_1 I(x_i = 0) + \pi_2\binom{N}{x_i}\hat{p}(t_i)^{x_i}(1 - \hat{p}(t_i))^{N - x_i}\right].$$

Based on a Taylor expansion of (4), similar to the proof of Theorem 3.2, we have that

$$\sqrt{n}(\tilde{\pi}_1 - \pi_1) = B_n^{-1}A_n + o_p(1).$$

where

$$\begin{aligned} A_n &= \frac{1}{\sqrt{n}}\sum_{i=1}^n \frac{\partial f(x_i, \pi_1, \hat{p}(t_i))}{\partial \pi_1} \\ B_n &= -\frac{1}{n}\sum_{i=1}^n \frac{\partial^2 f(x_i, \pi_1, \hat{p}(t_i))}{\partial \pi_1^2} \end{aligned}$$

It can be shown that

$$\begin{aligned} B_n &= -\mathrm{E}\left\{\frac{\partial^2 f(x_i, \pi_1, p(t_i))}{\partial \pi_1^2}\right\} + o_p(1) \\ &= \mathcal{I}_{\pi_1} + o_p(1). \end{aligned}$$

It can be shown that

$$\begin{aligned} A_n &= \frac{1}{\sqrt{n}}\sum_{i=1}^n \frac{\partial f(x_i, \pi_1, p(t_i))}{\partial \pi_1} + \frac{1}{\sqrt{n}}\sum_{i=1}^n \frac{\partial^2 f(x_i, \pi_1, p(t_i))}{\partial \pi_1 \partial p}\left\{\hat{p}(t_i) - p(t_i)\right\} + O_p(d_{1n}) \\ &= \frac{1}{\sqrt{n}}\sum_{i=1}^n \frac{\partial f(x_i, \pi_1, p(t_i))}{\partial \pi_1} + S_{n1} + O_p(d_{1n}). \end{aligned}$$

where $d_{1n} = n^{-1/2}||\tilde{\pi}_1 - \pi_1||_\infty^2 = o_p(1)$. Based on the proof of Theorem 3.2, we have

$$\hat{\boldsymbol{\theta}}(t_i) - \boldsymbol{\theta}(t_i) = \frac{1}{n} g(t_i)^{-1} \mathcal{I}(t_i)^{-1} \sum_{j=1}^{n} K_h(t_j - t_i) l_1(x_j, \boldsymbol{\theta}(t_i)) + O_p(d_{n2}),$$

Based on Carroll et al. (1997) and Li and Liang (2008), we have that $n^{1/2} d_{n2} = o_p(1)$ uniformly in t_i, if $nh^2/\log(1/h) \to \infty$. Let $\psi(t_j, x_j)$ be the second entry of $\mathcal{I}(t_j)^{-1} l_1(x_j, \boldsymbol{\theta}(t_j))$. Since $p(t_i) - p(t_j) = O(t_i - t_j)$ and $K(\cdot)$ is symmetric about 0, we have

$$\begin{aligned} S_{n1} &= \frac{1}{n^{-3/2}} \sum_{j=1}^{n} \sum_{i=1}^{n} \frac{\partial^2 f(x_i, \pi_1, p(t_i))}{\partial \pi_1 \partial p} g(t_i)^{-1} \psi(t_j, x_j) K_h(t_j - t_i) + O_p(n^{1/2} h^2) \\ &= S_{n2} + O_p(n^{1/2} h^2). \end{aligned}$$

It can be shown, by calculating the second moment, that

$$S_{n2} - S_{n3} = o_p(1),$$

where $S_{n3} = -n^{-1/2} \sum_{j=1}^{n} \xi(t_j, x_j)$, with

$$\begin{aligned} \xi(t_j, x_j) &= -\mathrm{E}\left\{ \frac{\partial^2 f(x, \pi_1, p(t_j))}{\partial \pi_1 \partial p} \mid t = t_j \right\} \psi(t_j, x_j) \\ &= \mathcal{I}_{\pi_1 p}(t_j) \psi(t_j, x_j). \end{aligned}$$

By condition $nh^4 \to 0$, we know

$$A_n = n^{-1/2} \sum_{i=1}^{n} \left\{ \frac{\partial f(x_i, \pi_1, p(t_i))}{\partial \pi_1} - \xi(t_i, x_i) \right\} + o_p(1).$$

We can show that $\mathrm{E}(A_n) = 0$. Define

$$\Sigma = \mathtt{var}(A_n) = \mathtt{var} \left\{ \frac{\partial f(x, \pi_1, p(t))}{\partial \pi_1} - \xi(t, x) \right\}.$$

Based on the central limit theorem, we can have

$$\sqrt{n}(\tilde{\pi}_1 - \pi_1) \to N(0, \mathcal{I}_{\pi_1}^{-2} \Sigma).$$

Proof of Theorem 3.4.
Based on a Taylor expansion of (7), similar to the proof of Theorem 3.2, we have

$$\sqrt{nh}\{\tilde{p}(t_0) - p(t_0)\} = g(t_0)^{-1} \mathcal{I}_p(t_0)^{-1} \tilde{W}_n (1 + o_p(1)),$$

where

$$\mathcal{I}_p(t) = -\mathrm{E}\left\{ \frac{\partial^2 f(x, \pi_1, p(t_0))}{\partial p^2} \Big| t \right\}$$

and

$$\tilde{W}_n = \sqrt{\frac{h}{n}} \sum_{i=1}^{n} \frac{\partial f(x_i, \pi_1, p(t_0))}{\partial p} K_h(t_i - t_0).$$

It can be calculated that

$$\tilde{W}_n = \sqrt{\frac{h}{n}} \sum_{i=1}^{n} \frac{\partial f(x_i, \tilde{\pi}_1, p(t_0))}{\partial p} K_h(t_i - t_0) + C_n + o_p(1),$$

where

$$C_n = \sqrt{\frac{h}{n}} \sum_{i=1}^{n} \frac{\partial^2 f(x_i, \pi_1, p(t_0))}{\partial p \partial \pi_1} (\tilde{\pi}_1 - \pi_1) K_h(t_i - t_0).$$

Since $\sqrt{n}(\tilde{\pi}_1 - \pi_1) = O_p(1)$, it can be shown that

$$C_n = o_p(1).$$

Hence

$$\sqrt{nh}\{\tilde{p}(t_0) - p(t_0)\} = g(t_0)^{-1} \mathcal{I}_p(t_0)^{-1} W_n (1 + o_p(1)),$$

where

$$W_n = \sqrt{\frac{h}{n}} \sum_{i=1}^{n} \frac{\partial f(x_i, \pi_1, p(t_0))}{\partial p} K_h(t_i - t_0).$$

Let

$$\Gamma(t) = \mathrm{E}\left\{ \frac{\partial f(x, \pi_1, p(t_0))}{\partial p} \Big| t \right\}.$$

Note that $\Gamma(t_0) = 0$. We can show that

$$\mathtt{var}(W_n) = \mathcal{I}_p(t_0) g(t_0) \nu_0 (1 + o_p(1))$$

and

$$\mathrm{E}(W_n) = \frac{\sqrt{nh}}{2} \{\Gamma''(t_0) g(t_0) + 2\Gamma'(t_0) g'(t_0)\} h^2 \mu_2 (1 + o_p(1)).$$

Similar to the proof of Theorem 3.2, we can prove the asymptotic normality of W_n. Hence, we have

$$\sqrt{nh}\{\tilde{p}(t_0) - p(t_0) - \tilde{b}(t_0) h^2\} \xrightarrow{D} N(0, g(t_0)^{-1} \mathcal{I}_p(t_0)^{-1} \nu_0),$$

where

$$\tilde{b}(t_0) = \frac{1}{2 g(t_0) \mathcal{I}_p(t_0)} \{\Gamma''(t_0) g(t_0) + 2\Gamma'(t_0) g'(t_0)\} \mu_2.$$