## CORRECTION ON

# ESTIMATION FOR A PARTIAL-LINEAR SINGLE-INDEX MODEL 

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This note is to correct an error in Lemma A. 7 of Wang et al. (2010). The original claim of asymptotically higher efficiency no longer holds.

Li and Yang found an error in the proof of Lemma A. 7 in Wang et al. (2010). The complete and compact proof provided in this correction note is due to Wang, Xue and Zhu, which was checked by all the authors. The error in the proof of Lemma A. 7 pertaining to the decomposition of $R_{3}\left(\beta^{(r)}\right)$. The key is that the derivative of the estimator of the single-index part $g\left(\beta^{T} X\right)$ about $\beta^{(r)}$ is not a proper estimator of the derivative $g^{\prime}\left(\beta^{T} X\right) X^{T} \mathbf{J}_{\beta^{(r)}}: \partial \hat{g}\left(\beta^{T} X ; \beta, \theta_{0}\right) / \partial \beta^{(r)} \neq$ $\hat{g}^{\prime}\left(\beta^{T} X ; \beta, \theta_{0}\right) X^{T} \mathbf{J}_{\beta^{(r)}}$, where $\mathbf{J}_{\beta^{(r)}}$ is the Jacobian matrix defined in the paper. Following a similar argument of decomposing $R\left(\beta^{(r)}\right)$ in the beginning of the proof of Lemma A.7, a detailed analysis shows that the matrix $\mathbf{V}$ in the result of Lemma A. 7 needs to be replaced by the matrix $\mathbf{Q}$. Thus, correcting the error leads to a change of the limiting variance of the estimator of $\beta$ and the original claim of asymptotically higher efficiency in the 2010 paper no longer holds. The new Lemma A. 7 and its proof are stated below.

LEMMA A.7. In addition to conditions C1-C6 in Wang et al. (2010), assume that $n h^{3} \rightarrow \infty$. Then we have

$$
\sup _{\beta^{(r)} \in \mathcal{B}_{n}}\left\|R\left(\beta^{(r)}\right)-U\left(\beta_{0}^{(r)}\right)+n \mathbf{Q}\left(\beta^{(r)}-\beta_{0}^{(r)}\right)\right\|=o_{P}(\sqrt{n})
$$

where $\mathcal{B}_{n}=\left\{\beta^{(r)}:\left\|\beta^{(r)}-\beta_{0}^{(r)}\right\| \leq C n^{-1 / 2}\right\}$ for a constant $C>0$,

$$
\begin{aligned}
\mathbf{Q} & =E\left\{g^{\prime}\left(\beta_{0}^{T} X\right)^{2} \mathbf{J}_{\beta_{0}^{(r)}}^{T}\left[X-E\left(X \mid \beta_{0}^{T} X\right)\right]\left[X-E\left(X \mid \beta_{0}^{T} X\right)\right]^{T} \mathbf{J}_{\beta_{0}^{(r)}}\right\}, \\
R\left(\beta^{(r)}\right) & =\sum_{i=1}^{n}\left[Y_{i}-Z_{i}^{T} \theta_{0}-\hat{g}\left(X_{i}^{T} \beta ; \beta, \theta_{0}\right)\right] \hat{g}^{\prime}\left(X_{i}^{T} \beta ; \beta, \theta_{0}\right) \mathbf{J}_{\beta^{(r)}}^{T} X_{i}
\end{aligned}
$$

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and

$$
U\left(\beta_{0}^{(r)}\right)=\sum_{i=1}^{n} e_{i} g^{\prime}\left(X_{i}^{T} \beta_{0}\right) \mathbf{J}_{\beta_{0}^{(r)}}^{T}\left[X_{i}-E\left(X_{i} \mid X_{i}^{T} \beta_{0}\right)\right]
$$

Proof. To prove this lemma, we adopt the notation in Cui et al. (2011), $\left.\frac{\partial \hat{g}\left(\beta^{T} X_{i} ; \beta, \theta_{0}\right)}{\partial \beta^{(r)}}\right|_{\beta=\beta_{0}}$ as the derivative, and other notation in Wang et al. (2010). Following the decomposition of $R\left(\beta^{(r)}\right)$, we now deal with $R_{3}\left(\beta^{(r)}\right)$. Note that the definition of $\mathcal{B}_{n}$ implies $\sup _{\beta^{(r)} \in \mathcal{B}_{n}^{(r)}}\left\|\beta^{(r)}-\beta_{0}^{(r)}\right\|=O\left(n^{-1 / 2}\right)$. An application of a Taylor expansion of $R_{3}\left(\beta^{(r)}\right)$ at $\beta_{0}^{(r)}$ leads to

$$
\begin{aligned}
R_{3}\left(\beta^{(r)}\right)= & \sum_{i=1}^{n} g^{\prime}\left(\beta_{0}^{T} X_{i}\right) \mathbf{J}_{\beta^{(r)}}^{T} X_{i}\left\{\hat{g}\left(\beta^{T} X_{i} ; \beta, \theta_{0}\right)-\hat{g}\left(\beta_{0}^{T} X_{i} ; \beta_{0}, \theta_{0}\right)\right\} \\
= & \sum_{i=1}^{n} g^{\prime}\left(\beta_{0}^{T} X_{i}\right) \mathbf{J}_{\beta_{0}^{(r)}}^{T} X_{i}\left\{\left.\left\{\frac{\partial \hat{g}\left(\beta^{T} X_{i} ; \beta, \theta_{0}\right)}{\partial \beta^{(r)}}\right\}^{T}\right|_{\beta=\beta_{0}}\right. \\
& \left.\quad-g^{\prime}\left(\beta_{0}^{T} X_{i}\right)\left[X_{i}-E\left(X_{i} \mid \beta_{0}^{T} X_{i}\right)\right]^{T} \mathbf{J}_{\beta_{0}^{(r)}}\right\} \\
& \times\left(\beta^{(r)}-\beta_{0}^{(r)}\right) \\
& +\sum_{i=1}^{n} g^{\prime}\left(\beta_{0}^{T} X_{i}\right)^{2} \mathbf{J}_{\beta_{0}^{(r)}}^{T} X_{i}\left[X_{i}-E\left(X_{i} \mid \beta_{0}^{T} X_{i}\right)\right]^{T} \mathbf{J}_{\beta_{0}^{(r)}}\left(\beta^{(r)}-\beta_{0}^{(r)}\right) \\
& +o_{P}(\sqrt{n}) \\
= & R_{31}\left(\beta^{(r)}\right)+R_{32}\left(\beta^{(r)}\right)+o_{P}(\sqrt{n})
\end{aligned}
$$

uniformly for $\beta^{(r)} \in \mathcal{B}_{n}$. By Proposition 1 in Cui et al. (2011), we can derive the following result: when $h \rightarrow 0$ and $n h^{3} \rightarrow \infty$, we have

$$
\begin{align*}
E\{\| & \left.\frac{\partial \hat{g}\left(\beta^{T} X_{i} ; \beta\right)}{\partial \beta^{(r)}}\right|_{\beta=\beta_{0}} \\
& \left.\quad-g^{\prime}\left(\beta_{0}^{T} X_{i}\right) \mathbf{J}_{\beta_{0}^{(r)}}^{T}\left[X_{i}-E\left(X_{i} \mid \beta_{0}^{T} X_{i}\right)\right] \|^{2} \mid \mathcal{X}\right\}=o_{P}(1) \tag{0.1}
\end{align*}
$$

for $i=1, \ldots, n$, where $\mathcal{X}=\left\{X_{1}, \ldots, X_{n}\right\}$. Invoking $\sup _{\beta^{(r)} \in \mathcal{B}_{n}^{(r)}}\left\|\beta^{(r)}-\beta_{0}^{(r)}\right\|=$ $O\left(n^{-1 / 2}\right)$ again, equation (0.1) and the law of large numbers yield that

$$
\sup _{\beta^{(r)} \in \mathcal{B}_{n}^{(r)}}\left\|R_{31}\left(\beta^{(r)}\right)\right\|=o_{P}(\sqrt{n})
$$

The law of large numbers is applied to $R_{32}\left(\beta^{(r)}\right)$ to derive

$$
\sup _{\beta^{(r)} \in \mathcal{B}_{n}^{(r)}}\left\|R_{32}\left(\beta^{(r)}\right)-n \mathbf{Q}\left(\beta^{(r)}-\beta_{0}^{(r)}\right)\right\|=o_{P}(\sqrt{n}) .
$$

Combining the above results, we get

$$
\sup _{\beta^{(r)} \in \mathcal{B}_{n}^{(r)}}\left\|R_{3}\left(\beta^{(r)}\right)-n \mathbf{Q}\left(\beta^{(r)}-\beta_{0}^{(r)}\right)\right\|=o_{P}(\sqrt{n}) .
$$

The proof is complete.
REMARK. The above proof shows that the matrix $\mathbf{V}$ in the old version of Lemma A. 7 should be replaced by $\mathbf{Q}$ and then the asymptotic normality in Theorem 2 in Wang et al. (2010) should be

$$
\sqrt{n}\left(\hat{\beta}-\beta_{0}\right) \xrightarrow{D} N\left(0, \sigma^{2} \mathbf{J}_{\beta_{0}^{(r)}} \mathbf{Q}^{-1} \mathbf{J}_{\beta_{0}^{(r)}}^{T}\right) .
$$

The corresponding limiting variance in the literature is $\sigma^{2} \mathbf{Q}_{1}^{-}$where

$$
\mathbf{Q}_{1}=E\left\{g^{\prime}\left(\beta_{0}^{T} X\right)^{2}\left[X-E\left(X \mid \beta_{0}^{T} X\right)\right]\left[X-E\left(X \mid \beta_{0}^{T} X\right)\right]^{T}\right\} .
$$

But this variance is not tractable. The result of Wang et al. (2010) gives a tractable form of the variance $\mathbf{J}_{\beta_{0}^{(r)}} \mathbf{Q}^{-1} \mathbf{J}_{\beta_{0}^{(r)}}^{T}$ when $\beta_{0}$ is re-parametrized.
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