

# Supplement to “Unconditional Quantile Regressions” \*

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November 2006

## Abstract

This supplement provides detailed derivation of the asymptotic properties of the estimators proposed in the article “Unconditional Quantile Regressions” by Firpo, Fortin and Lemieux.

**Keywords:** *Influence Functions, Unconditional Quantile, Quantile Regressions.*

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\*We are indebted to Richard Blundell, David Card, Vinicius Carrasco, Marcelo Fernandes, Chuan Goh, Joel Horowitz, Shakeeb Khan, Roger Koenker, Thierry Magnac, Whitney Newey, Geert Ridder, Jean-Marc Robin, Hal White and participants at the CESG 2005 Meeting, CAEN-UFC, Econometrics in Rio 2006 and UFMG for useful comments.

# 1 Large-sample properties of estimators of $UQPE(\tau)$

The first obvious aspect of the three estimation methods of  $UQPE(\tau)$  is that all of them are based on using sample quantities  $\widehat{f}_Y(\widehat{q}_\tau)$  and  $\widehat{q}_\tau$ . The density appears in the estimation of the parameter  $c_{1,\tau}$  whereas the sample quantile is important by itself in the replacement of  $T_\tau$  by  $\widehat{T}_\tau$ . Because the estimated density is used instead of the true one, our  $UQPE(\tau)$  estimators will be nonparametric in essence, and therefore will converge at a slower rate than the usual parametric estimator. We will state the results regarding order of convergence and the asymptotic distribution of our estimators. Before that, we invoke the following assumptions that will be used throughout this appendix and that concern the distribution of  $Y$ .

**ASSUMPTION 1 [Conditions on the distribution of  $Y$ ]** (i)  $F_Y(\cdot)$  is absolutely continuous and differentiable over  $y \in \mathbb{R}$  and  $f_Y(y) = dF_Y(y)/dy$ ; (ii)  $\int y \cdot f_Y(y) \cdot dy < \infty$ ; (iii)  $f_Y(\cdot)$  is uniformly continuous; (iv)  $\int |f_Y(y)| \cdot dy < \infty$ ; (v)  $f_Y(\cdot)$  is three times differentiable with bounded third derivative in a neighborhood of  $y$ ; (vi) for  $\tau \in (0, 1)$ , the sets  $\Upsilon_\tau = \inf_q \{F_Y(q) \geq \tau\}$ , are singletons and their elements  $q_\tau \in \Upsilon_\tau$  satisfy  $q_\tau < \infty$  and  $f_Y(q_\tau) > 0$ .

We divide this section into several parts to facilitate the exposition. The first part concerns the rate of convergence and the limiting distribution of the components of  $\widehat{\text{RIF}}(y, \widehat{q}_\tau)$ . Then we establish the results for the estimators of  $UQPE(\tau)$ .

## 1.1 Components of $\widehat{\text{RIF}}(y, \widehat{q}_\tau)$

All estimators will involve  $\widehat{f}_Y(\widehat{q}_\tau)$  and  $\widehat{q}_\tau$  whenever  $\widehat{c}_{1,\tau}$ ,  $\widehat{T}$  and  $\widehat{c}_{2,\tau}$  are used. We now establish some useful results regarding the limiting behavior of those quantities. Before that, let us suppose the following set of assumptions hold.

**ASSUMPTION 2 [Kernel Function and Bandwidth]** (i)  $K_Y(\cdot)$  is a bounded real-valued function satisfying (a)  $\int K_Y(y) \cdot dy = 1$ , (b)  $\int |K_Y(y)| \cdot dy < \infty$ , (c)  $\int K_Y^2(y) \cdot dy < \infty$ , (d)  $\lim_{y \rightarrow \pm\infty} |y| \cdot |K_Y(y)| = 0$ , (e)  $\sup_y |K_Y(y)| < \infty$ , (f)  $K_Y(y) = \frac{1}{2\pi} \int \exp(-i \cdot t \cdot y) \cdot \phi(t) \cdot dt$ , where  $\phi(t)$  is the absolutely integrable characteristic function of  $K_Y(\cdot)$ ; (ii)  $b_Y$  is a bandwidth sequence satisfying  $b_Y = O(N^{-a})$ ,  $a < 1$ , and  $\lim_{N \rightarrow +\infty} \sqrt{N \cdot b_Y} \cdot b_Y^2 = 0$ .

Now consider each individual component of  $\widehat{\text{RIF}}(y, \widehat{q}_\tau) = \widehat{c}_{1,\tau} \cdot \widehat{T}_\tau + \widehat{c}_{2,\tau}$ :

1.  $\widehat{c}_{1,\tau} - c_{1,\tau}$

We have

$$\begin{aligned}\widehat{c}_{1,\tau} &= c_{1,\tau} + \frac{1}{\widehat{f}_Y(\widehat{q}_\tau)} - \frac{1}{f_Y(q_\tau)} \\ &= c_{1,\tau} + \frac{1}{\widehat{f}_Y(q_\tau)} - \frac{\widehat{f}'_Y(q_\tau)}{\widehat{f}_Y^2(q_\tau)} \cdot (\widehat{q}_\tau - q_\tau) - \frac{1}{f_Y(q_\tau)} + \eta_1,\end{aligned}$$

where

$$\eta_1 = - \left( \frac{\widehat{f}'_Y(\widetilde{q}_\tau)}{\widehat{f}_Y^2(\widetilde{q}_\tau)} - \frac{\widehat{f}'_Y(q_\tau)}{\widehat{f}_Y^2(q_\tau)} \right) \cdot (\widehat{q}_\tau - q_\tau) = O_p(|\widetilde{q}_\tau - q_\tau| \cdot |\widehat{q}_\tau - q_\tau|).$$

Note also that

$$\frac{1}{\widehat{f}_Y(q_\tau)} = \frac{1}{f_Y(q_\tau)} - \frac{1}{f_Y^2(q_\tau)} \cdot \left( \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right) + \eta_2,$$

with

$$\begin{aligned}\eta_2 &= - \left( \frac{1}{\widehat{f}_Y^2(q_\tau)} - \frac{1}{f_Y^2(q_\tau)} \right) \cdot \left( \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right) \\ &= O_p\left( \left| \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right| \cdot \left| \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right| \right),\end{aligned}$$

and, therefore,

$$\frac{1}{\widehat{f}_Y^2(q_\tau)} = \frac{1}{f_Y^2(q_\tau)} - \frac{2}{f_Y^3(q_\tau)} \cdot \left( \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right) + \eta'_2,$$

with

$$\begin{aligned}\eta'_2 &= -2 \cdot \left( \frac{1}{\widehat{f}_Y^3(q_\tau)} - \frac{1}{f_Y^3(q_\tau)} \right) \cdot \left( \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right) \\ &= O_p\left( \left| \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right| \cdot \left| \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right| \right).\end{aligned}$$

Thus

$$\begin{aligned}
\widehat{c}_{1,\tau} &= c_{1,\tau} - \frac{1}{f_Y^2(q_\tau)} \cdot (\widehat{f}_Y(q_\tau) - f_Y(q_\tau)) \\
&\quad - \widehat{f}'_Y(q_\tau) \cdot (\widehat{q}_\tau - q_\tau) \cdot \left( \frac{1}{f_Y^2(q_\tau)} - \frac{2}{f_Y^3(q_\tau)} \cdot (\widehat{f}_Y(q_\tau) - f_Y(q_\tau)) + \eta'_2 \right) + \eta_1 + \eta_2 \\
&= c_{1,\tau} - \frac{1}{f_Y(q_\tau)} \cdot \frac{(\widehat{f}_Y(q_\tau) - f_Y(q_\tau))}{f_Y(q_\tau)} \\
&\quad - \frac{1}{f_Y(q_\tau)} \cdot \left( 1 - 2 \cdot \frac{(\widehat{f}_Y(q_\tau) - f_Y(q_\tau))}{f_Y(q_\tau)} \right) \cdot \frac{\widehat{f}'_Y(q_\tau)}{f_Y(q_\tau)} \cdot (\widehat{q}_\tau - q_\tau) + \eta_1 + \eta_2 + \eta_3,
\end{aligned}$$

where

$$\eta_3 = -\eta'_2 \cdot \widehat{f}'_Y(q_\tau) \cdot (\widehat{q}_\tau - q_\tau) = O_p \left( |\widehat{q}_\tau - q_\tau| \cdot \left| \widehat{f}'_Y(q_\tau) - f'_Y(q_\tau) \right| \cdot \left| \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right| \right).$$

Finally, because

$$\begin{aligned}
\widehat{f}'_Y(q_\tau) &= f'_Y(q_\tau) + \widehat{f}'_Y(q_\tau) - f'_Y(q_\tau) \\
&= f'_Y(q_\tau) + \eta_4,
\end{aligned}$$

with

$$\eta_4 = \widehat{f}'_Y(q_\tau) - f'_Y(q_\tau) = O_p \left( \left| \widehat{f}'_Y(q_\tau) - f'_Y(q_\tau) \right| \right),$$

we have that

$$\begin{aligned}
\widehat{c}_{1,\tau} &= c_{1,\tau} - \frac{1}{f_Y(q_\tau)} \cdot \frac{\left(\widehat{f}_Y(q_\tau) - f_Y(q_\tau)\right)}{f_Y(q_\tau)} \\
&\quad - \frac{1}{f_Y(q_\tau)} \cdot \left(1 - 2 \cdot \frac{\left(\widehat{f}_Y(q_\tau) - f_Y(q_\tau)\right)}{f_Y(q_\tau)}\right) \cdot \frac{f'_Y(q_\tau)}{f_Y(q_\tau)} \cdot (\widehat{q}_\tau - q_\tau) \\
&\quad - \frac{1}{f_Y(q_\tau)} \cdot \left(1 - 2 \cdot \frac{\left(\widehat{f}_Y(q_\tau) - f_Y(q_\tau)\right)}{f_Y(q_\tau)}\right) \cdot \frac{(\widehat{q}_\tau - q_\tau)}{f_Y(q_\tau)} \cdot \eta_4 \\
&\quad + \eta_1 + \eta_2 + \eta_3 \\
&= c_{1,\tau} - \frac{1}{f_Y(q_\tau)} \cdot \frac{\left(\widehat{f}_Y(q_\tau) - f_Y(q_\tau)\right)}{f_Y(q_\tau)} \\
&\quad - \frac{1}{f_Y(q_\tau)} \cdot \left(1 - 2 \cdot \frac{\left(\widehat{f}_Y(q_\tau) - f_Y(q_\tau)\right)}{f_Y(q_\tau)}\right) \cdot \frac{f'_Y(q_\tau)}{f_Y(q_\tau)} \cdot (\widehat{q}_\tau - q_\tau) \\
&\quad + \eta_1 + \eta_2 + \eta_3 + \eta_5 \\
&= c_{1,\tau} - \frac{1}{f_Y(q_\tau)} \cdot \frac{\left(\widehat{f}_Y(q_\tau) - f_Y(q_\tau)\right)}{f_Y(q_\tau)} - \frac{1}{f_Y(q_\tau)} \cdot \frac{f'_Y(q_\tau)}{f_Y(q_\tau)} \cdot (\widehat{q}_\tau - q_\tau) + \eta,
\end{aligned}$$

where

$$\begin{aligned}
\eta_5 &= -\frac{1}{f_Y^2(q_\tau)} \cdot \left(1 - 2 \cdot \frac{\left(\widehat{f}_Y(q_\tau) - f_Y(q_\tau)\right)}{f_Y(q_\tau)}\right) \cdot \eta_4 \cdot (\widehat{q}_\tau - q_\tau) \\
&= O_p\left(\eta_4 \cdot |\widehat{q}_\tau - q_\tau| \cdot \left|\widehat{f}_Y(q_\tau) - f_Y(q_\tau)\right|\right) \\
&= O_p\left(\left|\widehat{f}'_Y(q_\tau) - f'_Y(q_\tau)\right| \cdot |\widehat{q}_\tau - q_\tau| \cdot \left|\widehat{f}_Y(q_\tau) - f_Y(q_\tau)\right|\right),
\end{aligned}$$

$$\begin{aligned}
\eta_6 &= 2 \cdot \frac{\left(\widehat{f}_Y(q_\tau) - f_Y(q_\tau)\right)}{f_Y^2(q_\tau)} \cdot \frac{f'_Y(q_\tau)}{f_Y(q_\tau)} \cdot (\widehat{q}_\tau - q_\tau) \\
&= O_p\left(|\widehat{q}_\tau - q_\tau| \cdot \left|\widehat{f}_Y(q_\tau) - f_Y(q_\tau)\right|\right),
\end{aligned}$$

$$\begin{aligned}
\eta &= \eta_1 + \eta_2 + \eta_3 + \eta_5 + \eta_6 \\
&= O_p(|\tilde{q}_\tau - q_\tau| \cdot |\hat{q}_\tau - q_\tau|) \\
&\quad + O_p\left(\left|\tilde{f}_Y(q_\tau) - f_Y(q_\tau)\right| \cdot \left|\hat{f}_Y(q_\tau) - f_Y(q_\tau)\right|\right) \\
&\quad + O_p\left(\left|\hat{f}'_Y(q_\tau) - f'_Y(q_\tau)\right| \cdot |\hat{q}_\tau - q_\tau| \cdot \left|\hat{f}_Y(q_\tau) - f_Y(q_\tau)\right|\right).
\end{aligned}$$

Now

$$\begin{aligned}
\hat{q}_\tau - q_\tau &= \frac{1}{N} \cdot \sum_{i=1}^N \frac{\tau - \mathbb{I}\{Y_i \leq q_\tau\}}{f_Y(q_\tau)} + o_p(N^{-1/2}) \\
&= \frac{1}{N} \cdot \sum_{i=1}^N \frac{T_{\tau,i} - (1 - \tau)}{f_Y(q_\tau)} + o_p(N^{-1/2}) \\
&= O_p(N^{-1/2}),
\end{aligned}$$

while

$$\begin{aligned}
\left|\hat{f}_Y(q_\tau) - f_Y(q_\tau)\right| &= \left|\hat{f}_Y(q_\tau) + E\left[\hat{f}_Y(q_\tau)\right] - \left(E\left[\hat{f}_Y(q_\tau)\right] - f_Y(q_\tau)\right)\right| \\
&\leq \left|\hat{f}_Y(q_\tau) + E\left[\hat{f}_Y(q_\tau)\right]\right| + \left|E\left[\hat{f}_Y(q_\tau)\right] - f_Y(q_\tau)\right| \\
&= O_p\left((N \cdot b_Y)^{-1/2}\right) + O(b_Y^2).
\end{aligned}$$

If we use a undersmoothing bandwidth that makes the bias vanishes faster than the variance (see Pagan and Ullah, 1999, for example), that is

$$(N \cdot b_Y)^{1/2} \cdot b_Y^2 \xrightarrow{N \rightarrow \infty} 0$$

$$b_Y = C \cdot N^{-a}, \quad 1 > a > 1/5,$$

then

$$\begin{aligned}
\left|\hat{f}_Y(q_\tau) - f_Y(q_\tau)\right| &= O_p(N^{(a-1)/2}) + O_p(N^{-2a}) \\
&= O_p(N^{(a-1)/2}),
\end{aligned}$$

and, therefore

$$(a - 1) / 2 > -2/5.$$

Also suppose that

$$O_p \left( \left| \widehat{f}'_Y(q_\tau) - f'_Y(q_\tau) \right| \right) = O_p(N^{-b}), \quad b > 0.$$

Then

$$\eta = O_p \left( N^{\max\{a-1, -1, a/2-1-b\}} \right) = O_p(N^{a-1}),$$

because since  $a > 1/5$  and  $b > 0$

$$a - 1 > -1$$

$$a - 1 > a/2 - 1 - b \Leftrightarrow a + 2b > 0 \Leftrightarrow a > 1/5 \text{ and } b > 0.$$

Now, we have

$$\begin{aligned} \widehat{c}_{1,\tau} &= c_{1,\tau} - \frac{1}{f_Y(q_\tau)} \cdot \frac{\left( \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right)}{f_Y(q_\tau)} - \frac{1}{f_Y(q_\tau)} \cdot \frac{f'_Y(q_\tau)}{f_Y(q_\tau)} \cdot (\widehat{q}_\tau - q_\tau) + \eta \\ &= c_{1,\tau} + O_p(N^{(a-1)/2}) + O_p(N^{-1/2}) + O_p(N^{a-1}). \end{aligned}$$

Finally

$$\begin{aligned} \widehat{c}_{1,\tau} - c_{1,\tau} &= -\frac{1}{f_Y(q_\tau)} \cdot \frac{\left( \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right)}{f_Y(q_\tau)} + o_p(N^{(a-1)/2}) \\ &= -\frac{1}{f_Y(q_\tau)} \cdot \frac{\left( \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right)}{f_Y(q_\tau)} + o_p\left( (N \cdot b_Y)^{-1/2} \right), \end{aligned}$$

and

$$\begin{aligned} \sqrt{N \cdot b_Y} \cdot (\widehat{c}_{1,\tau} - c_{1,\tau}) &= -\frac{1}{f_Y^2(q_\tau)} \cdot \left( \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right) + o_p(1) \\ &\xrightarrow{D} N \left( 0, \frac{1}{f_Y^3(q_\tau)} \cdot \int K_Y^2(z) \cdot dz \right). \end{aligned}$$

2.  $\widehat{c}_{2,\tau} - c_{2,\tau}$

We have

$$\begin{aligned}
\widehat{c}_{2,\tau} &= c_{2,\tau} + \widehat{q}_\tau + \widehat{c}_{1,\tau} \cdot (\tau - 1) - (q_\tau + c_{1,\tau} \cdot (\tau - 1)) \\
&= c_{2,\tau} + \widehat{q}_\tau - q_\tau + (\tau - 1) \cdot (\widehat{c}_{1,\tau} - c_{1,\tau}) \\
&= c_{2,\tau} + O_p(N^{-1/2}) + O_p(N^{(a-1)/2}) \\
&= c_{2,\tau} + O_p(N^{(a-1)/2}).
\end{aligned}$$

Thus

$$\widehat{c}_{2,\tau} - c_{2,\tau} = (\tau - 1) \cdot (\widehat{c}_{1,\tau} - c_{1,\tau}) + o_p(N^{(a-1)/2}),$$

and

$$\begin{aligned}
\sqrt{N \cdot b_Y} \cdot (\widehat{c}_{2,\tau} - c_{2,\tau}) &= \frac{(1 - \tau)}{f_Y^2(q_\tau)} \cdot \left( \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right) + o_p(1) \\
&\xrightarrow{D} N \left( 0, \frac{(1 - \tau)^2}{f_Y^3(q_\tau)} \cdot \int K_Y^2(z) \cdot dz \right).
\end{aligned}$$

$$3. \frac{1}{N} \cdot \sum_{i=1}^N \left( \widehat{T}_{\tau,i} - T_{\tau,i} \right)$$

Define

$$R(Y_i, \widehat{q}_\tau, q_\tau) \equiv \widehat{T}_{\tau,i} - T_{\tau,i}.$$

Then

$$\begin{aligned}
&\left| \frac{1}{\sqrt{N}} \cdot \sum_{i=1}^N (R(Y_i, \widehat{q}_\tau, q_\tau) - E[R(Y, \widehat{q}_\tau, q_\tau)]) \right| \\
&\leq O_p \left( \left( E \left[ E \left[ R^2(Y, \widehat{q}_\tau, q_\tau) \mid \widehat{q}_\tau \right] \right] \right)^{1/2} \right) \\
&= O_p \left( \left( E \left[ \Pr[q_\tau < Y \leq \widehat{q}_\tau \mid \widehat{q}_\tau] \right] \right)^{1/2} \right) \\
&= O_p \left( \left( E \left[ \sup_{\widehat{q}_\tau \in \mathbb{R}} f_Y|_{\widehat{q}_\tau}(\widetilde{q}_\tau | \widehat{q}_\tau) \mid \widehat{q}_\tau \right] \cdot |\widehat{q}_\tau - q_\tau| \right)^{1/2} \right) \\
&= O_p \left( |\widehat{q}_\tau - q_\tau|^{1/2} \right) \\
&= O_p(N^{-1/4}),
\end{aligned}$$



so

$$\begin{aligned}
& \left| \frac{1}{N} \cdot \sum_{i=1}^N R(Y_i, \hat{q}_\tau, q_\tau) \right| \\
& \leq |E[R(Y, \hat{q}_\tau, q_\tau)]| + N^{-1/2} \cdot \left| \frac{1}{\sqrt{N}} \cdot \sum_{i=1}^N (R(Y_i, \hat{q}_\tau, q_\tau) - E[R(Y, \hat{q}_\tau, q_\tau)]) \right| \\
& = O_p(|E[R^2(Y, \hat{q}_\tau, q_\tau)]|) + O_p(N^{-3/4}) \\
& = O_p(|\hat{q}_\tau - q_\tau|) + O_p(N^{-3/4}) = O_p(N^{-1/2}) + O_p(N^{-3/4}) \\
& = O_p(N^{-1/2}).
\end{aligned}$$

Thus

$$\begin{aligned}
\frac{1}{N} \cdot \sum_{i=1}^N (\hat{T}_{\tau,i} - T_{\tau,i}) &= \hat{q}_\tau - q_\tau + o_p(N^{-1/2}) \\
&= \frac{1}{N} \cdot \sum_{i=1}^N \frac{T_{\tau,i} - (1-\tau)}{f_Y(q_\tau)} + o_p(N^{-1/2}) \\
&\xrightarrow{D} N \left( 0, \frac{\tau \cdot (1-\tau)}{f_Y^2(q_\tau)} \right).
\end{aligned}$$

## 1.2 RIF – OLS: asymptotics

Specific assumptions for the particular estimators RIF – OLS are:

ASSUMPTION 3 [RIF – **OLS**] (i)  $E[X \cdot X^\top]$  is invertible and (ii)  $Cov[X \cdot \mathbf{1}\{Y > q_\tau\}] \neq 0$ , (iii)  $E[\text{vec}(X \cdot X^\top) \cdot \text{vec}(X \cdot X^\top)^\top] < \infty$ ,  $E[X \cdot X^\top \cdot \mathbf{1}\{Y > q_\tau\}] < \infty$ ; (iv)  $c_{1,\tau} \cdot E[\mathbf{1}\{Y > q_\tau\} | X = x] + c_{2,\tau} = x^\top \gamma_\tau$ .

The key result of this subsection is:

PROPOSITION 1 [RIF – **OLS**] Under assumptions 1, 2 and 3

$$\begin{aligned}
& \sqrt{N \cdot b_Y} \cdot (\hat{\gamma}_\tau - \gamma_\tau) \xrightarrow{D} \\
& N \left( 0, (E[X \cdot X^\top])^{-1} Cov[X, T_\tau] \cdot Cov[X, T_\tau]^\top \cdot (E[X \cdot X^\top])^{-1} \cdot f_Y^{-3}(q_\tau) \cdot \int K_Y^2(z) \cdot dz \right)
\end{aligned}$$

**Proof of Proposition 1:** We divide the proof into two parts. We first find the convergence rate of the estimator and then derive its asymptotic distribution.

### 1.2.1 Order of convergence

The difference between the estimator and the population parameter is

$$\widehat{\gamma}_\tau - \gamma_\tau = \widehat{\gamma}_\tau - \widetilde{\gamma}_\tau + \widetilde{\gamma}_\tau - \gamma_\tau$$

where we define  $\widetilde{\gamma}_\tau$  as the coefficient that we would compute if we were using the true RIF:

$$\widetilde{\gamma}_\tau = \left( \sum_{i=1}^N X_i \cdot X_i^\top \right)^{-1} \cdot \sum_{i=1}^N X_i \cdot \text{RIF}(Y_i; q_\tau),$$

and  $\gamma_\tau$  is

$$\gamma_\tau = (E[X \cdot X^\top])^{-1} \cdot E[X \cdot \text{RIF}(Y; q_\tau)].$$

The first term  $\widehat{\gamma}_\tau - \widetilde{\gamma}_\tau$  can be obtained by rewriting  $\widehat{\gamma}_\tau$  as

$$\begin{aligned} \widehat{\gamma}_\tau &= \left( \sum_{i=1}^N X_i \cdot X_i^\top \right)^{-1} \cdot \sum_{i=1}^N X_i \cdot \widehat{\text{RIF}}(Y_i; \widehat{q}_\tau) \\ &= \left( \sum_{i=1}^N X_i \cdot X_i^\top \right)^{-1} \cdot \sum_{i=1}^N X_i \cdot \text{RIF}(Y_i; q_\tau) \\ &\quad + \left( \sum_{i=1}^N X_i \cdot X_i^\top \right)^{-1} \cdot \sum_{i=1}^N X_i \cdot \left( \widehat{\text{RIF}}(Y_i; \widehat{q}_\tau) - \text{RIF}(Y_i; q_\tau) \right) \\ &= \widetilde{\gamma}_\tau + \left( \sum_{i=1}^N X_i \cdot X_i^\top \right)^{-1} \cdot \sum_{i=1}^N X_i \cdot \left( (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot \widehat{T}_{\tau,i} + c_{1,\tau} \cdot (\widehat{T}_{\tau,i} - T_{\tau,i}) + \widehat{c}_{2,\tau} - c_{2,\tau} \right) \\ &= \widetilde{\gamma}_\tau + \left( \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot X_i^\top \right)^{-1} \\ &\quad \cdot \sum_{i=1}^N X_i \cdot \left( (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot (\widehat{T}_{\tau,i} - (1 - \tau)) + c_{1,\tau} \cdot (\widehat{T}_{\tau,i} - T_{\tau,i}) + \widehat{q}_\tau - q_\tau \right) \end{aligned}$$

therefore

$$\begin{aligned}
& \|\widehat{\gamma}_\tau - \widetilde{\gamma}_\tau\| \\
&= \left( \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot X_i^\top \right)^{-1} \cdot \left( (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot (\widehat{T}_{\tau,i} - (1 - \tau)) \right. \\
&\quad \left. + \frac{c_{1,\tau}}{N} \cdot \sum_{i=1}^N X_i \cdot (\widehat{T}_{\tau,i} - T_{\tau,i}) + (\widehat{q}_\tau - q_\tau) \cdot \frac{1}{N} \cdot \sum_{i=1}^N X_i \right) \\
&\leq C \cdot |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot (T_{\tau,i} - (1 - \tau)) \right\| \\
&\quad + C \cdot |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot (\widehat{T}_{\tau,i} - T_{\tau,i}) \right\| \\
&\quad + C \cdot \left\| \frac{c_{1,\tau}}{N} \cdot \sum_{i=1}^N X_i \cdot (\widehat{T}_{\tau,i} - T_{\tau,i}) \right\| + C \cdot |\widehat{q}_\tau - q_\tau| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N X_i \right\|,
\end{aligned}$$

but

$$\begin{aligned}
& \left\| \frac{1}{\sqrt{N}} \cdot \left( \sum_{i=1}^N X_i \cdot (\widehat{T}_{\tau,i} - T_{\tau,i}) - E[X \cdot (\widehat{T}_\tau - T_\tau)] \right) \right\| \\
&= \left\| \frac{1}{\sqrt{N}} \cdot \sum_{i=1}^N (X_i \cdot R(Y_i, \widehat{q}_\tau, q_\tau) - E[X \cdot R(Y, \widehat{q}_\tau, q_\tau)]) \right\| \\
&\leq O_p \left( \left\| E[X \cdot X^\top \cdot E[E[R^2(Y, \widehat{q}_\tau, q_\tau) | \widehat{q}_\tau, X] | X]] \right\|^{1/2} \right) \\
&= O_p \left( \left\| E[X \cdot X^\top \cdot E[\Pr[q_\tau < Y \leq \widehat{q}_\tau | \widehat{q}_\tau, X] | X]] \right\|^{1/2} \right) \\
&= O_p \left( \left\| E \left[ E \left[ X \cdot X^\top \cdot E \left[ \sup_{\widehat{q}_\tau \in \mathbb{R}} f_{Y|\widehat{q}_\tau, X}(\widehat{q}_\tau | \widehat{q}_\tau, X) | \widehat{q}_\tau, X \right] | X \right] \right] \cdot |\widehat{q}_\tau - q_\tau| \right\|^{1/2} \right) \\
&= \|E[X \cdot X^\top]\|^{1/2} \cdot O_p \left( |\widehat{q}_\tau - q_\tau|^{1/2} \right) \\
&= O_p \left( |\widehat{q}_\tau - q_\tau|^{1/2} \right) \\
&= O_p \left( N^{-1/4} \right),
\end{aligned}$$

and, therefore

$$\begin{aligned}
& \left\| \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot (\widehat{T}_{\tau,i} - T_{\tau,i}) \right\| \\
& \leq \left\| E \left[ X \cdot (\widehat{T}_\tau - T_\tau) \right] \right\| + N^{-1/2} \cdot \left\| \frac{1}{\sqrt{N}} \cdot \left( \sum_{i=1}^N X_i \cdot (\widehat{T}_{\tau,i} - T_{\tau,i}) - E \left[ X \cdot (\widehat{T}_\tau - T_\tau) \right] \right) \right\| \\
& = O_p \left( |E [X \cdot R^2(Y, \widehat{q}_\tau, q_\tau)]| \right) + O_p \left( N^{-3/4} \right) \\
& = \|E [X]\| \cdot O_p(|\widehat{q}_\tau - q_\tau|) + O_p \left( N^{-3/4} \right) = O_p(1) \cdot O_p \left( N^{-1/2} \right) + O_p \left( N^{-3/4} \right) \\
& = O_p \left( N^{-1/2} \right).
\end{aligned}$$

Thus

$$\begin{aligned}
\|\widehat{\gamma}_\tau - \widetilde{\gamma}_\tau\| &= O_p(|\widehat{c}_{1,\tau} - c_{1,\tau}|) \cdot O_p(1) + O_p(|\widehat{c}_{1,\tau} - c_{1,\tau}|) \cdot O_p \left( N^{-1/2} \right) + O_p \left( N^{-1/2} \right) \\
&= O_p \left( N^{(a-1)/2} \right) + O_p \left( N^{-1/2} \right).
\end{aligned}$$

Since  $a > 1/5$ , it follows that

$$|\widehat{\gamma}_\tau - \widetilde{\gamma}_\tau| = O_p \left( N^{(a-1)/2} \right).$$

Now we look at the second term,

$$\begin{aligned}
\|\widetilde{\gamma}_\tau - \gamma_\tau\| &= \left\| \left( \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot X_i^\top \right)^{-1} \cdot \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot \text{RIF}(Y_i; q_\tau) - \gamma_\tau \right\| \\
&\leq \left\| \left( \left( \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot X_i^\top \right)^{-1} - (E[X \cdot X^\top])^{-1} \right) \cdot \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot \text{RIF}(Y_i; q_\tau) \right\| \\
&\quad + \left\| (E[X \cdot X^\top])^{-1} \cdot \left( \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot \text{RIF}(Y_i; q_\tau) - E[X \cdot \text{RIF}(Y; q_\tau)] \right) \right\| \\
&\leq \frac{1}{\sqrt{N}} \cdot \left\| \sqrt{N} \cdot \left( \left( \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot X_i^\top \right)^{-1} - (E[X \cdot X^\top])^{-1} \right) \right\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot \text{RIF}(Y_i; q_\tau) \right\| \\
&\quad + \frac{1}{\sqrt{N}} \cdot \|(E[X \cdot X^\top])^{-1}\| \cdot \left\| \sqrt{N} \cdot \left( \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot \text{RIF}(Y_i; q_\tau) - E[X \cdot \text{RIF}(Y; q_\tau)] \right) \right\| \\
&= N^{-1/2} \cdot O_p(1) \cdot O_p(1) + N^{-1/2} \cdot O_p(1) \cdot O_p(1) \\
&= O_p \left( N^{-1/2} \right).
\end{aligned}$$

Therefore

$$\widehat{\gamma}_\tau - \gamma_\tau = O_p(N^{(a-1)/2}),$$

that is, the difference between the feasible and the unfeasible estimators determines the rate of convergence.

### 1.2.2 Asymptotic Distribution

$$\widehat{\gamma}_\tau - \gamma_\tau = (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot \left( \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot X_i^\top \right)^{-1} \cdot \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot (T_{\tau,i} - (1 - \tau)) + o_p(N^{(a-1)/2}),$$

so we have that

$$\begin{aligned} & \sqrt{N \cdot b_Y} \cdot (\widehat{\gamma}_\tau - \gamma_\tau) \\ &= (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot (E[X \cdot X^\top])^{-1} \cdot \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot (T_{\tau,i} - (1 - \tau)) + o_p(1) \\ &= -\frac{1}{f_Y^2(q_\tau)} \cdot (E[X \cdot X^\top])^{-1} \cdot Cov[X, T_\tau] \cdot \sqrt{N \cdot b_Y} \cdot (\widehat{f}_Y(q_\tau) - f_Y(q_\tau)) \\ & \quad - \frac{(E[X \cdot X^\top])^{-1}}{f_Y^2(q_\tau)} \cdot \sqrt{N \cdot b_Y} \cdot (\widehat{f}_Y(q_\tau) - f_Y(q_\tau)) \\ & \quad \cdot \left( \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot (T_{\tau,i} - (1 - \tau)) - Cov[X, T_\tau] \right) + o_p(1) \\ &= -\frac{1}{f_Y^2(q_\tau)} \cdot (E[X \cdot X^\top])^{-1} \cdot Cov[X, T_\tau] \cdot \sqrt{N \cdot b_Y} \cdot (\widehat{f}_Y(q_\tau) - f_Y(q_\tau)) + o_p(1) \\ & \xrightarrow{D} N(0, V_{OLS}), \end{aligned}$$

where

$$\begin{aligned} V_{OLS} &= f_Y^{-3}(q_\tau) \cdot (E[X \cdot X^\top])^{-1} \cdot Cov[X, T_\tau] \cdot Cov[X, T_\tau]^\top \cdot (E[X \cdot X^\top])^{-1} \cdot \int K_Y^2(z) \cdot dz \\ &= (\gamma_\tau - (1 - \tau)) \cdot (E[X \cdot X^\top])^{-1} \cdot E[X] \cdot (\gamma_\tau - (1 - \tau)) \cdot (E[X \cdot X^\top])^{-1} \cdot E[X]^\top \\ & \quad \cdot f_Y^{-3}(q_\tau) \cdot \int K_Y^2(z) \cdot dz, \end{aligned}$$

and

$$\begin{aligned}
\text{Cov}[X, T_\tau] &= E[\mathbb{I}\{Y > q_\tau\} \cdot X] - (1 - \tau) \cdot E[X] \\
m_\tau(x) &= E[E[\mathbb{I}\{Y > q_\tau\} | X] \cdot X] - (1 - \tau) \cdot E[X] \\
&= E[\text{Pr}[Y > q_\tau | X] \cdot X] - \text{Pr}[Y > q_\tau] \cdot E[X] \\
&= E[m_\tau(X) \cdot X] - (1 - \tau) \cdot E[X] \\
&= E[X \cdot X^\top] \cdot \gamma_\tau - (1 - \tau) E[X].
\end{aligned}$$

■

### 1.3 RIF – *logit*: asymptotics

We make the following assumptions:

ASSUMPTION 4 [RIF – **Logit**] (i)  $E[(\Lambda''(X^\top \theta_\tau^*))^2 \cdot X \cdot X^\top]$  is invertible for all  $\theta_\tau^* \in \mathbb{R}^k$ , (ii)  $E[(1 - \Lambda(X^\top \theta_\tau))^2 \cdot \Lambda^2(X^\top \theta_\tau)] < \infty$ , (iii)  $E[\mathbb{I}\{Y > q_\tau\} | X = x] = \Lambda(x^\top \theta_\tau)$ .

The key result of this subsection is:

PROPOSITION 2 [RIF – **Logit**] Under assumptions 1, 2 and 4

$$\begin{aligned}
&\sqrt{N \cdot b_Y} \cdot \left( \widehat{UQPE}_{\text{RIF-logit}}(\tau) - UQPE(\tau) \right) \xrightarrow{D} \\
&N \left( 0, f_Y^{-3}(q_\tau) \cdot E[\Lambda'(X^\top \theta_\tau)]^2 \cdot \theta_\tau \cdot \theta_\tau^\top \cdot \int K_Y^2(z) \cdot dz \right)
\end{aligned}$$

**Proof of Proposition 2:** We divide the proof into two parts. We first find the convergence rate of the estimator and then derive its asymptotic distribution.

### 1.3.1 Order of convergence

We estimate  $UQPE(\tau)$  under the logistic assumption as  $\widehat{UQPE}_{\text{RIF-logit}}(\tau)$ , where<sup>1</sup>

$$\widehat{UQPE}_{\text{RIF-logit}}(\tau) = \widehat{c}_{1,\tau} \cdot \widehat{\theta}_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \widehat{\theta}_\tau).$$

An unfeasible estimator of  $UQPE(\tau)$  uses the unobservable variable  $T_\tau$  instead of  $\widehat{T}_\tau$  and the true constant  $c_{1,\tau}$  instead of  $\widehat{c}_{1,\tau}$ . We call the unfeasible estimator  $\widetilde{UQPE}_{\text{RIF-logit}}(\tau)$ :

$$\widetilde{UQPE}_{\text{RIF-logit}}(\tau) = c_{1,\tau} \cdot \widetilde{\theta}_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \widetilde{\theta}_\tau),$$

where

$$\widetilde{\theta}_\tau = \arg \max_{\theta_\tau} \sum_i T_{\tau,i} \cdot X_i^\top \theta_\tau + \log(1 - \Lambda(X_i^\top \theta_\tau)).$$

We now find the probability order of  $\widehat{UQPE}_{\text{RIF-logit}} - UQPE(\tau)$ :

$$\begin{aligned} & \left\| \widehat{UQPE}_{\text{RIF-logit}} - UQPE(\tau) \right\| \\ & \leq \left\| \widehat{UQPE}_{\text{RIF-logit}} - \widetilde{UQPE}_{\text{RIF-logit}}(\tau) \right\| + \left\| \widetilde{UQPE}_{\text{RIF-logit}}(\tau) - UQPE(\tau) \right\|, \end{aligned}$$

where

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<sup>1</sup>Remember that by the properties of the logistic distribution:

$$\begin{aligned} \Lambda'(z) &= \Lambda(z) \cdot (1 - \Lambda(z)) \\ \Lambda''(z) &= \Lambda'(z) \cdot (1 - 2 \cdot \Lambda(z)) \end{aligned}$$

$$\begin{aligned}
& \left\| \widehat{UQPE}_{\text{RIF-logit}} - \widetilde{UQPE}_{\text{RIF-logit}}(\tau) \right\| \\
&= \left\| \widehat{c}_{1,\tau} \cdot \widehat{\theta}_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda' \left( X_i^\top \widehat{\theta}_\tau \right) - c_{1,\tau} \cdot \widetilde{\theta}_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda' \left( X_i^\top \widetilde{\theta}_\tau \right) \right\| \\
&\leq \left\| (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot \widehat{\theta}_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda' \left( X_i^\top \widehat{\theta}_\tau \right) \right\| \\
&\quad + c_{1,\tau} \cdot \left\| \widehat{\theta}_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda' \left( X_i^\top \widehat{\theta}_\tau \right) - \widetilde{\theta}_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda' \left( X_i^\top \widetilde{\theta}_\tau \right) \right\| \\
&\leq \left\| (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot \widetilde{\theta}_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda' \left( X_i^\top \widehat{\theta}_\tau \right) \right\| + \left\| (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot (\widehat{\theta}_\tau - \widetilde{\theta}_\tau) \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda' \left( X_i^\top \widehat{\theta}_\tau \right) \right\| \\
&\quad + c_{1,\tau} \cdot \left\| (\widehat{\theta}_\tau - \widetilde{\theta}_\tau) \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda' \left( X_i^\top \widehat{\theta}_\tau \right) \right\| + c_{1,\tau} \cdot \left\| \widetilde{\theta}_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \left( \Lambda' \left( X_i^\top \widehat{\theta}_\tau \right) - \Lambda' \left( X_i^\top \widetilde{\theta}_\tau \right) \right) \right\|.
\end{aligned}$$

Thus

$$\begin{aligned}
& \left\| \widehat{UQPE}_{\text{RIF-logit}} - \widetilde{UQPE}_{\text{RIF-logit}}(\tau) \right\| \\
&\leq \left\| (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot \theta_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda' \left( X_i^\top \widehat{\theta}_\tau \right) \right\| \\
&\quad + \left\| (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot (\widetilde{\theta}_\tau - \theta_\tau) \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda' \left( X_i^\top \widehat{\theta}_\tau \right) \right\| \\
&\quad + \left\| (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot (\widehat{\theta}_\tau - \widetilde{\theta}_\tau) \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda' \left( X_i^\top \widehat{\theta}_\tau \right) \right\| \\
&\quad + c_{1,\tau} \cdot \left\| (\widehat{\theta}_\tau - \widetilde{\theta}_\tau) \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda' \left( X_i^\top \widehat{\theta}_\tau \right) \right\| \\
&\quad + c_{1,\tau} \cdot \left\| \theta_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \left( \Lambda' \left( X_i^\top \widehat{\theta}_\tau \right) - \Lambda' \left( X_i^\top \widetilde{\theta}_\tau \right) \right) \right\| \\
&\quad + c_{1,\tau} \cdot \left\| (\widetilde{\theta}_\tau - \theta_\tau) \cdot \frac{1}{N} \cdot \sum_{i=1}^N \left( \Lambda' \left( X_i^\top \widehat{\theta}_\tau \right) - \Lambda' \left( X_i^\top \widetilde{\theta}_\tau \right) \right) \right\|,
\end{aligned}$$



and, therefore

$$\begin{aligned}
& \left\| \widehat{UQPE}_{\text{RIF-logit}} - \widetilde{UQPE}_{\text{RIF-logit}}(\tau) \right\| \\
\leq & |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \|\theta_\tau\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) \right| \\
& + |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \|\theta_\tau\| \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\| \\
& + |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \left\| \widetilde{\theta}_\tau - \theta_\tau \right\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) \right| \\
& + |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\| \cdot \left\| \widetilde{\theta}_\tau - \theta_\tau \right\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\| \\
& + |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) \right| \\
& + |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\|^2 \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\| \\
& + c_{1,\tau} \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) \right| + c_{1,\tau} \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\|^2 \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\| \\
& + c_{1,\tau} \cdot \|\theta_\tau\| \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\| \\
& + c_{1,\tau} \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\| \cdot \left\| \widetilde{\theta}_\tau - \theta_\tau \right\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\|,
\end{aligned}$$

where  $\theta_\tau^*$  is an intermediate value between  $\widehat{\theta}_\tau$  and  $\widetilde{\theta}_\tau$ . We now give names to the terms above and find their convergence rates:

$$\begin{aligned}
\varphi_1 &= |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \|\theta_\tau\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) \right|, \\
\varphi_2 &= |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \|\theta_\tau\| \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\|, \\
\varphi_3 &= |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \left\| \widetilde{\theta}_\tau - \theta_\tau \right\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) \right|,
\end{aligned}$$

$$\begin{aligned}
\varphi_4 &= |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\| \cdot \left\| \widetilde{\theta}_\tau - \theta_\tau \right\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\|, \\
\varphi_5 &= |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) \right|, \\
\varphi_6 &= |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\|^2 \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\|, \\
\varphi_7 &= c_{1,\tau} \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) \right|, \\
\varphi_8 &= c_{1,\tau} \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\|^2 \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\|, \\
\varphi_9 &= c_{1,\tau} \cdot \left\| \theta_\tau \right\| \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\|, \\
\varphi_{10} &= c_{1,\tau} \cdot \left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\| \cdot \left\| \widetilde{\theta}_\tau - \theta_\tau \right\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\|.
\end{aligned}$$

Now we find a bound for the difference  $\widehat{\theta}_\tau - \widetilde{\theta}_\tau$ . Remember first that the first order conditions imply that  $\widehat{\theta}_\tau$  and  $\widetilde{\theta}_\tau$  are solutions to:

$$\begin{aligned}
\sum_{i=1}^N X_i^\top \cdot \left( \widehat{T}_{\tau,i} - \Lambda \left( X_i^\top \widehat{\theta}_\tau \right) \right) &= 0 \\
\sum_{i=1}^N X_i^\top \cdot \left( T_{\tau,i} - \Lambda \left( X_i^\top \widetilde{\theta}_\tau \right) \right) &= 0.
\end{aligned}$$

Thus,

$$\begin{aligned}
& \sum_{i=1}^N X_i \cdot \left( \widehat{T}_{\tau,i} - \Lambda \left( X_i^\top \widehat{\theta}_\tau \right) \right) \\
&= \sum_{i=1}^N X_i \cdot \left( T_{\tau,i} - \Lambda \left( X_i^\top \widehat{\theta}_\tau \right) + \left( \widehat{T}_{\tau,i} - T_{\tau,i} \right) \right) \\
&= \sum_{i=1}^N X_i \cdot \left( T_{\tau,i} - \Lambda \left( X_i^\top \widetilde{\theta}_\tau \right) - X_i^\top \cdot \Lambda' \left( X_i^\top \theta_\tau^* \right) \cdot \left( \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right) + \left( \widehat{T}_{\tau,i} - T_{\tau,i} \right) \right) \\
&= - \sum_{i=1}^N X_i \cdot \left( X_i^\top \cdot \Lambda' \left( X_i^\top \theta_\tau^* \right) \cdot \left( \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right) - \left( \widehat{T}_{\tau,i} - T_{\tau,i} \right) \right) = 0
\end{aligned}$$

The difference between the two solutions  $\widehat{\theta}_\tau$  and  $\widetilde{\theta}_\tau$  is:

$$\begin{aligned}
& \widehat{\theta}_\tau - \widetilde{\theta}_\tau \\
&= \left( \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot X_i^\top \cdot \Lambda' \left( X_i^\top \theta_\tau^* \right) \right)^{-1} \cdot \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot \left( \widehat{T}_{\tau,i} - T_{\tau,i} \right).
\end{aligned}$$

Thus

$$\begin{aligned}
\left\| \widehat{\theta}_\tau - \widetilde{\theta}_\tau \right\| &\leq C \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N X_i \cdot \left( \widehat{T}_{\tau,i} - T_{\tau,i} \right) \right\| \\
&= O_p \left( |\widehat{q}_\tau - q_\tau| \right) \cdot O_p \left( 1 \right) \\
&= O_p \left( N^{-1/2} \right),
\end{aligned}$$

and the difference between the maximum likelihood estimator and the parameter will also be  $O_p \left( N^{-1/2} \right)$ , that is,

$$\left\| \widetilde{\theta}_\tau - \theta_\tau \right\| = O_p \left( N^{-1/2} \right).$$

Now we find the convergence order of each of the previous terms of the sum, from  $\varphi_1$  to  $\varphi_{10}$ :

$$\begin{aligned}
\varphi_1 &= |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \|\theta_\tau\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda' \left( X_i^\top \theta_\tau \right) \right| \\
&= O_p \left( N^{(a-1)/2} \right) \cdot O_p \left( 1 \right) \cdot O_p \left( 1 \right) = O_p \left( N^{(a-1)/2} \right),
\end{aligned}$$

$$\begin{aligned}
\varphi_2 &= |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \|\theta_\tau\| \cdot \|\widehat{\theta}_\tau - \widetilde{\theta}_\tau\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\| \\
&= O_p(N^{(a-1)/2}) \cdot O_p(1) \cdot O_p(N^{-1/2}) \cdot O_p(1) = O_p(N^{a/2-1}),
\end{aligned}$$

$$\begin{aligned}
\varphi_3 &= |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \|\widetilde{\theta}_\tau - \theta_\tau\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) \right| \\
&= O_p(N^{(a-1)/2}) \cdot O_p(N^{-1/2}) \cdot O_p(1) = O_p(N^{a/2-1}),
\end{aligned}$$

$$\begin{aligned}
\varphi_4 &= |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \|\widehat{\theta}_\tau - \widetilde{\theta}_\tau\| \cdot \|\widetilde{\theta}_\tau - \theta_\tau\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\| \\
&= O_p(N^{(a-1)/2}) \cdot O_p(N^{-1/2}) \cdot O_p(N^{-1/2}) \cdot O_p(1) = O_p(N^{(a-3)/2}),
\end{aligned}$$

$$\begin{aligned}
\varphi_5 &= |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \|\widehat{\theta}_\tau - \widetilde{\theta}_\tau\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) \right| \\
&= O_p(N^{(a-1)/2}) \cdot O_p(N^{-1/2}) \cdot O_p(1) = O_p(N^{a/2-1}),
\end{aligned}$$

$$\begin{aligned}
\varphi_6 &= |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \|\widehat{\theta}_\tau - \widetilde{\theta}_\tau\|^2 \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\| \\
&= O_p(N^{(a-1)/2}) \cdot O_p(N^{-1}) \cdot O_p(1) = O_p(N^{(a-3)/2}),
\end{aligned}$$

$$\begin{aligned}
\varphi_7 &= c_{1,\tau} \cdot \|\widehat{\theta}_\tau - \widetilde{\theta}_\tau\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) \right| \\
&= O_p(1) \cdot O_p(N^{-1/2}) \cdot O_p(1) = O_p(N^{-1/2}),
\end{aligned}$$

$$\begin{aligned}
\varphi_8 &= c_{1,\tau} \cdot \|\widehat{\theta}_\tau - \widetilde{\theta}_\tau\|^2 \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\| \\
&= O_p(1) \cdot O_p(N^{-1}) \cdot O_p(1) = O_p(N^{-1}),
\end{aligned}$$

$$\begin{aligned}
\varphi_9 &= c_{1,\tau} \cdot \|\theta_\tau\| \cdot \|\widehat{\theta}_\tau - \widetilde{\theta}_\tau\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\| \\
&= O_p(1) \cdot O_p(1) \cdot O_p(N^{-1/2}) \cdot O_p(1) = O_p(N^{-1/2}),
\end{aligned}$$

$$\begin{aligned}
\varphi_{10} &= c_{1,\tau} \cdot \|\widehat{\theta}_\tau - \widetilde{\theta}_\tau\| \cdot \|\widetilde{\theta}_\tau - \theta_\tau\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^*) \cdot X_i^\top \right\| \\
&= O_p(N^{-1/2}) \cdot O_p(N^{-1/2}) \cdot O_p(1) = O_p(N^{-1}).
\end{aligned}$$

Thus, the order of convergence of  $\left| \widehat{UQPE}_{\text{RIF-logit}} - \widetilde{UQPE}_{\text{RIF-logit}}(\tau) \right|$  is  $O_p(N^{(a-1)/2})$ .

We now find the order of convergence of the next part of the sum:

$$\begin{aligned}
& \left| \widetilde{UQPE}_{\text{RIF-logit}}(\tau) - UQPE(\tau) \right| \\
&= \left| c_{1,\tau} \cdot \widetilde{\theta}_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \widetilde{\theta}_\tau) - c_{1,\tau} \cdot \theta_\tau \cdot E[\Lambda'(X^\top \theta_\tau)] \right| \\
&= c_{1,\tau} \cdot \left| (\widetilde{\theta}_\tau - \theta_\tau) \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \widetilde{\theta}_\tau) + \theta_\tau \cdot \left( \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \widetilde{\theta}_\tau) - E[\Lambda'(X^\top \theta_\tau)] \right) \right| \\
&\leq c_{1,\tau} \cdot \|\widetilde{\theta}_\tau - \theta_\tau\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) \right| + c_{1,\tau} \cdot \|\widetilde{\theta}_\tau - \theta_\tau\|^2 \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^{**}) \cdot X_i^\top \right\| \\
&\quad + c_{1,\tau} \cdot \|\theta_\tau\| \cdot \left( \frac{1}{N} \cdot \sum_{i=1}^N (\Lambda'(X_i^\top \theta_\tau) - E[\Lambda'(X^\top \theta_\tau)]) \right) \\
&\quad + c_{1,\tau} \cdot \|\theta_\tau\| \cdot \|\widetilde{\theta}_\tau - \theta_\tau\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda''(X_i^\top \theta_\tau^{**}) \cdot X_i^\top \right\| \\
&= O_p(1) \cdot O_p(N^{-1/2}) \cdot O_p(1) + O_p(1) \cdot O_p(N^{-1}) \cdot O_p(1) \\
&\quad + O_p(1) \cdot O_p(1) \cdot O_p(N^{-1/2}) + O_p(1) \cdot O_p(1) \cdot O_p(N^{-1/2}) \cdot O_p(1) \\
&= O_p(N^{-1/2}).
\end{aligned}$$

Thus

$$\begin{aligned}
\left\| \widehat{UQPE}_{\text{RIF-logit}} - UQPE(\tau) \right\| &= \left\| (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot \theta_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) \right\| + o_p(N^{(a-1)/2}) \\
&= O_p(N^{(a-1)/2}).
\end{aligned}$$

### 1.3.2 Asymptotic Normality

$$\begin{aligned}
& \sqrt{N \cdot b_Y} \cdot \left( \widehat{UQPE}_{\text{RIF-logit}} - UQPE(\tau) \right) \\
&= \sqrt{N \cdot b_Y} \cdot (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot \theta_\tau \cdot \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) + o_p(1) \\
&= \sqrt{N \cdot b_Y} \cdot (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot \theta_\tau \cdot E[\Lambda'(X^\top \theta_\tau)] \\
&\quad + \sqrt{N \cdot b_Y} \cdot (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot \theta_\tau \cdot \left( \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(X_i^\top \theta_\tau) - E[\Lambda'(X^\top \theta_\tau)] \right) + o_p(1) \\
&= \sqrt{N \cdot b_Y} \cdot (\widehat{c}_{1,\tau} - c_{1,\tau}) \cdot \theta_\tau \cdot E[\Lambda'(X^\top \theta_\tau)] + o_p(1) \\
&= -\frac{\theta_\tau \cdot E[\Lambda'(X^\top \theta_\tau)]}{f_Y^2(q_\tau)} \cdot \sqrt{N \cdot b_Y} \cdot \left( \widehat{f}_Y(q_\tau) - f_Y(q_\tau) \right) + o_p(1) \\
&\xrightarrow{D} N \left( 0, f_Y^{-3}(q_\tau) \cdot E[\Lambda'(X^\top \theta_\tau)]^2 \cdot \theta_\tau \cdot \theta_\tau^\top \cdot \int K_Y^2(z) \cdot dz \right).
\end{aligned}$$

■

## 1.4 RIF – NP: asymptotics

PROPOSITION 3 [RIF – NP] *Under the assumptions for the Sieve-series approximation in Hirano, Imbens and Ridder (2003, Assumption 5) and assumptions 1 and, 2*

$$\begin{aligned}
& \widehat{UQPE}_{\text{RIF-NP}}(\tau) - UQPE(\tau) \\
&= \frac{1}{N} \cdot \sum_{i=1}^N (H_{K(\tau)}(X_i)^\top \cdot (\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau))) \cdot (H'_{K(\tau)}(X_i)^\top \cdot \rho_K(\tau)) \cdot \Lambda''(H_{K(\tau)}(X_i)^\top \rho_K^{**}(\tau)) \\
&\quad + o_p(N^{3c-1/2}).
\end{aligned}$$

**Proof of Proposition 3:**

### 1.4.1 Order of convergence

We estimate  $UQPE(\tau)$  nonparametrically by means of  $\widehat{UQPE}_{\text{RIF-NP}}(\tau)$ :

$$\widehat{UQPE}_{\text{RIF-NP}}(\tau) = \widehat{c}_{1,\tau} \cdot \frac{1}{N} \cdot \sum_{i=1}^N \frac{d\Pr[T_\tau = 1 | X = X_i]}{dx},$$

where the nonparametric estimate of  $d\Pr [T_\tau = 1|X = x] / dx$  is

$$\frac{d\Pr [T_\tau = 1|X = x]}{dx} = \widehat{\rho}_K(\tau) \cdot H'_{K(\tau)}(x)^\top \cdot \Lambda' (H_{K(\tau)}(x)^\top \widehat{\rho}_K(\tau)).$$

An unfeasible nonparametric estimator of  $UQPE(\tau)$  is  $\widetilde{UQPE}_{\text{RIF-NP}}(\tau)$ :

$$\widetilde{UQPE}_{\text{RIF-NP}}(\tau) = \widehat{c}_{1,\tau} \cdot \frac{1}{N} \cdot \sum_{i=1}^N \frac{d\Pr [T_\tau = 1|X = X_i]}{dx},$$

$$\frac{d\Pr [T_\tau = 1|X = x]}{dx} = \widetilde{\rho}_K(\tau) \cdot \frac{dH_{K(\tau)}(x)^\top}{dx} \cdot \Lambda' (H_{K(\tau)}(x)^\top \widetilde{\rho}_K(\tau)),$$

where

$$\widetilde{\rho}_K(\tau) = \arg \max_{\rho_K(\tau)} \sum_i^N T_{\tau,i} \cdot H_{K(\tau)}(X_i)^\top \rho_K(\tau) + \log (1 - \Lambda (H_{K(\tau)}(X_i)^\top \rho_K(\tau))).$$

We now establish the order of convergence of  $\widehat{UQPE}_{\text{RIF-NP}}(\tau) - \widetilde{UQPE}_{\text{RIF-NP}}(\tau)$ :

$$\begin{aligned} & \left\| \widehat{UQPE}_{\text{RIF-NP}}(\tau) - \widetilde{UQPE}_{\text{RIF-NP}}(\tau) \right\| \\ & \leq |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \left\| \frac{UQPE(\tau)}{c_{1,\tau}} \right\| \\ & + |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \left( \frac{d\Pr [T_\tau = 1|X = X_i]}{dx} - \frac{UQPE(\tau)}{c_{1,\tau}} \right) \right\| \\ & + c_{1,\tau} \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \left( \frac{d\Pr [T_\tau = 1|X = x]}{dx} - \frac{d\Pr [T_\tau = 1|X = X_i]}{dx} \right) \right\| \\ & + |\widehat{c}_{1,\tau} - c_{1,\tau}| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \left( \frac{d\Pr [T_\tau = 1|X = x]}{dx} - \frac{d\Pr [T_\tau = 1|X = X_i]}{dx} \right) \right\|. \end{aligned}$$

Note that

$$\left\| \frac{1}{N} \cdot \sum_{i=1}^N \left( \frac{d\Pr [T_\tau = 1|X = X_i]}{dx} - \frac{UQPE(\tau)}{c_{1,\tau}} \right) \right\| = O_p(N^{-1/2}),$$

as the unfeasible estimator will simply be an average derivative estimator whose properties have been already established in the literature (Härdle and Stoker, 1989). The key

is to derive the order of convergence of

$$\begin{aligned}
& \left\| \frac{1}{N} \cdot \sum_{i=1}^N \left( \frac{d \Pr [T_\tau = 1 | X = x]}{dx} - \frac{d \Pr [T_\tau = 1 | X = X_i]}{dx} \right) \right\| \\
& \leq \|\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau)\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot \Lambda' (H_{K(\tau)}(X_i)^\top \widetilde{\rho}_K(\tau)) \right\| \\
& + \|\widehat{\rho}_K(\tau)\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot (\Lambda' (H_{K(\tau)}(X_i)^\top \widehat{\rho}_K(\tau)) - \Lambda' (H_{K(\tau)}(X_i)^\top \widetilde{\rho}_K(\tau))) \right\| \\
& \leq \|\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau)\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot \Lambda' (H_{K(\tau)}(X_i)^\top \rho_K(\tau)) \right\| \\
& + \|\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau)\| \cdot \|\widetilde{\rho}_K(\tau) - \rho_K(\tau)\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot H_{K(\tau)}(X_i) \cdot \Lambda'' (H_{K(\tau)}(X_i)^\top \rho_K^*(\tau)) \right\| \\
& + \|\rho_K(\tau)\| \cdot \|\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau)\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot H_{K(\tau)}(X_i) \cdot \Lambda'' (H_{K(\tau)}(X_i)^\top \rho_K^{**}(\tau)) \right\| \\
& + \|\widetilde{\rho}_K(\tau) - \rho_K(\tau)\| \cdot \|\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau)\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot H_{K(\tau)}(X_i) \cdot \Lambda'' (H_{K(\tau)}(X_i)^\top \rho_K^{**}(\tau)) \right\| \\
& + \|\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau)\|^2 \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot H_{K(\tau)}(X_i) \cdot \Lambda'' (H_{K(\tau)}(X_i)^\top \rho_K^{**}(\tau)) \right\|,
\end{aligned}$$

where  $\rho_K(\tau)$  is the pseudo true value  $\rho_K(\tau)$  as

$$\rho_K(\tau) \equiv \arg \max_{\rho} E \left[ [\Pr [T_\tau = 1 | X] \cdot H_{K(\tau)}(X)^\top \rho + \log (1 - \Lambda (H_{K(\tau)}(X)^\top \rho))] \right].$$

Consider the following arguments:

1. Order of  $\|(\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau))\|$  :

$$\begin{aligned}
\widehat{\rho}_K(\tau) &= \arg_{\rho_K} \text{zero} \sum_{i=1}^N H_{K(\tau)}(X_i)^\top \cdot \left( \widehat{T}_{\tau,i} - \Lambda (H_{K(\tau)}(X_i)^\top \rho_K(\tau)) \right) \\
\widetilde{\rho}_K(\tau) &= \arg_{\rho_K} \text{zero} \sum_{i=1}^N H_{K(\tau)}(X_i)^\top \cdot (T_{\tau,i} - \Lambda (H_{K(\tau)}(X_i)^\top \rho_K(\tau))).
\end{aligned}$$



Thus,

$$\begin{aligned}
& \widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau) \\
&= \left( \sum_{i=1}^N H_{K(\tau)}(X_i) \cdot H_{K(\tau)}(X_i)^\top \cdot \Lambda' \left( H_{K(\tau)}(X_i)^\top \rho_K^*(\tau) \right) \right)^{-1} \\
&\quad \cdot \sum_{i=1}^N H_{K(\tau)}(X_i)^\top \cdot \left( \widehat{T}_{\tau,i} - T_{\tau,i} \right)
\end{aligned}$$

Thus, to find the order of convergence of this term, we proceed as follows:

$$\begin{aligned}
& \|(\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau))\| \\
&= \left\| \left( \frac{1}{N} \cdot \sum_{i=1}^N H_{K(\tau)}(X_i) \cdot H_{K(\tau)}(X_i)^\top \cdot \Lambda' \left( H_{K(\tau)}(X_i)^\top \rho_K^*(\tau) \right) \right)^{-1} \right. \\
&\quad \left. \cdot \frac{1}{N} \cdot \sum_{i=1}^N H_{K(\tau)}(X_i)^\top \cdot R(Y_i, \widehat{q}_\tau, q_\tau) \right\| \\
&\leq C \cdot \left\| \sup_{x \in \mathcal{X}} H_{K(\tau)}(x) \right\| \cdot \left| \frac{1}{N} \cdot \sum_{i=1}^N R(Y_i, \widehat{q}_\tau, q_\tau) \right| \\
&= O_p(\Gamma(K) \cdot N^{-1/2}) = O_p(K(N) \cdot N^{-1/2}) \\
&= O_p(N^{c-1/2}),
\end{aligned}$$

where

$$\left\| \sup_{x \in \mathcal{X}} H_{K(\tau)}(x) \right\| = \Gamma(K) = O(K),$$

but the length of the vector of polynomials depends on  $N$  at the following way:

$$K(N) = O_p(N^c), \quad c > 0.$$

2. Order of  $\|\widetilde{\rho}_K(\tau) - \rho_K(\tau)\|$  and of  $\|\rho_K(\tau)\|$  :

We have

$$\widetilde{\rho}_K(\tau) = \rho_K(\tau) + \widetilde{\rho}_K(\tau) - \rho_K(\tau),$$

but remember that

$$\begin{aligned}
0 &= \sum_{i=1}^N H_{K(\tau)}(X_i) \cdot (T_{\tau,i} - \Lambda(H_{K(\tau)}(X_i)^\top \tilde{\rho}_K(\tau))) \\
&= \sum_{i=1}^N H_{K(\tau)}(X_i) \cdot \left( T_{\tau,i} - \Lambda(H_{K(\tau)}(X_i)^\top \rho_K(\tau)) - \Lambda'(H_{K(\tau)}(X_i)^\top \rho_K^*(\tau)) \right. \\
&\quad \left. \cdot H_{K(\tau)}(X_i)^\top (\tilde{\rho}_K(\tau) - \rho_K(\tau)) \right).
\end{aligned}$$

Thus

$$\begin{aligned}
\tilde{\rho}_K(\tau) - \rho_K(\tau) &= \left( \frac{1}{N} \cdot \sum_{i=1}^N H_{K(\tau)}(X_i) \cdot H_{K(\tau)}(X_i)^\top \cdot \Lambda'(H_{K(\tau)}(X_i)^\top \rho_K^*(\tau)) \right)^{-1} \\
&\quad \cdot \frac{1}{N} \cdot \sum_{i=1}^N H_{K(\tau)}(X_i)^\top \cdot (T_{\tau,i} - \Lambda(H_{K(\tau)}(X_i)^\top \rho_K(\tau))).
\end{aligned}$$

But

$$\begin{aligned}
&E \left[ \left\| \frac{1}{\sqrt{N}} \cdot \sum_{i=1}^N H_{K(\tau)}(X_i)^\top \cdot (T_{\tau,i} - \Lambda(H_{K(\tau)}(X_i)^\top \rho_K(\tau))) \right\|^2 \right] \\
&= \text{tr} \left( E \left[ H_{K(\tau)}(X) \cdot H_{K(\tau)}(X)^\top \cdot \Lambda'(H_{K(\tau)}(X)^\top \rho_K(\tau)) \right] \right) \\
&\leq C \cdot K,
\end{aligned}$$

as  $H_{K(\tau)}(X)$  is a rotation of an orthogonal polynomial. Now under the hypothesis that  $K^4/N \rightarrow 0$

$$\|\tilde{\rho}_K(\tau) - \rho_K(\tau)\| = O_p\left((K/N)^{1/2}\right).$$

Now consider the difference between  $\rho_K(\tau)$  and  $\rho_{0,K}(\tau)$  where is such that, according to Newey (1995, 1997):

$$\sup_{x \in \mathcal{X}} \left| \ln(\Pr[T_\tau = 1|X]) - \ln(1 - \Pr[T_\tau = 1|X]) - H_{K(\tau)}(X)^\top \rho_{0,K}(\tau) \right| \leq C \cdot K^{-s/k}$$

where  $s$  is the number of derivatives of  $m_\tau(x)$ , and  $k$  the length of  $X$ . Following Hirano, Imbens, and Ridder (2003):

$$\|\rho_K(\tau) - \rho_{0,K}(\tau)\| \leq C \cdot K^{-s/(2r)}.$$

Thus

$$\begin{aligned}
\|\rho_K(\tau)\| &\leq \|\rho_K(\tau) - \rho_{0,K}(\tau)\| + \|\rho_{0,K}(\tau)\| \\
&= O(K^{-s/(2r)}) + \Gamma(K) \\
&= O(K).
\end{aligned}$$

3. Order of  $\left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot \Lambda'(H_{K(\tau)}(X_i)^\top \rho_K(\tau)) \right\|$ :

$$\begin{aligned}
&\left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(H_{K(\tau)}(X_i)^\top \rho_K(\tau)) \cdot H'_{K(\tau)}(X_i)^\top \right\| \\
&\leq C \cdot \left\| \sup_{x \in \mathcal{X}} H_{K(\tau)}(x) \right\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N \Lambda'(H_{K(\tau)}(X_i)^\top \rho_K(\tau)) \right\| \\
&\leq O(K) \cdot O_p(1) = O_P(N^c)
\end{aligned}$$

4. Order of  $\left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot H_{K(\tau)}(X_i) \cdot \Lambda''(H_{K(\tau)}(X_i)^\top \rho_K^{**}(\tau)) \right\|$ :

The derivative vector  $H'_{K(\tau)}(x)$  is just a linear combination of the original polynomial vector

$$H'_{K(\tau)}(x) = A \cdot H_{K(\tau)}(x).$$

Therefore

$$\begin{aligned}
&\left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot H_{K(\tau)}(X_i) \cdot \Lambda''(H_{K(\tau)}(X_i)^\top \rho_K^{**}(\tau)) \right\| \\
&\leq C \cdot \text{tr} \left( E \left[ H_{K(\tau)}(X) \cdot H_{K(\tau)}(X)^\top \cdot \Lambda''(H_{K(\tau)}(X)^\top \rho_K(\tau)) \right] \right) \\
&\quad + C \cdot \|\xi\| \\
&= O(K) + O_p(\|\xi\|) = O_p(K(N)) + o_p(K(N)) \\
&= O_p(N^c),
\end{aligned}$$

where

$$\begin{aligned}
\xi &= \frac{1}{N} \cdot \sum_{i=1}^N H_{K(\tau)}(X_i)^\top \cdot H_{K(\tau)}(X_i) \cdot \Lambda''(H_{K(\tau)}(X_i)^\top \rho_K^{**}(\tau)) \\
&\quad - E \left[ H_{K(\tau)}(X) \cdot H_{K(\tau)}(X)^\top \cdot \Lambda''(H_{K(\tau)}(X)^\top \rho_K(\tau)) \right].
\end{aligned}$$

Finally

$$\begin{aligned} & \|\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau)\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot \Lambda' (H_{K(\tau)}(X_i)^\top \rho_K(\tau)) \right\| \\ &= O_p(N^{c-1/2}) \cdot O_p(N^c) = O_p(N^{2c-1/2}), \end{aligned}$$

$$\begin{aligned} & \|\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau)\| \\ & \cdot \|\widetilde{\rho}_K(\tau) - \rho_K(\tau)\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot H_{K(\tau)}(X_i) \cdot \Lambda'' (H_{K(\tau)}(X_i)^\top \rho_K^*(\tau)) \right\| \\ &= O_p(N^{c-1/2}) \cdot O_p(N^{(c-1)/2}) \cdot O_p(N^c) = O_p(N^{5c-1}), \end{aligned}$$

$$\begin{aligned} & \|\rho_K(\tau)\| \cdot \|\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau)\| \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot H_{K(\tau)}(X_i) \cdot \Lambda'' (H_{K(\tau)}(X_i)^\top \rho_K^{**}(\tau)) \right\| \\ &= O(N^c) \cdot O_p(N^{c-1/2}) \cdot O_p(N^c) = O_p(N^{3c-1/2}), \end{aligned}$$

$$\begin{aligned} & \|\widetilde{\rho}_K(\tau) - \rho_K(\tau)\| \cdot \|\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau)\| \\ & \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot H_{K(\tau)}(X_i) \cdot \Lambda'' (H_{K(\tau)}(X_i)^\top \rho_K^{**}(\tau)) \right\| \\ &= O_p(N^{(c-1)/2}) \cdot O_p(N^{c-1/2}) \cdot O_p(N^c) = O_p(N^{5c-1}), \end{aligned}$$

$$\begin{aligned} & \|\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau)\|^2 \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot H_{K(\tau)}(X_i) \cdot \Lambda'' (H_{K(\tau)}(X_i)^\top \rho_K^{**}(\tau)) \right\| \\ &= O_p(N^{2c-1}) \cdot O_p(N^c) = O_p(N^{3c-1}). \end{aligned}$$

Thus

$$\begin{aligned} & \left\| \frac{1}{N} \cdot \sum_{i=1}^N \left( \frac{d \Pr [T_\tau = 1 | X = x]}{dx} - \frac{d \Pr [T_\tau = 1 | X = X_i]}{dx} \right) \right\| \\ &= \|\rho_K(\tau)\| \cdot \|\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau)\| \\ & \cdot \left\| \frac{1}{N} \cdot \sum_{i=1}^N H'_{K(\tau)}(X_i)^\top \cdot H_{K(\tau)}(X_i) \cdot \Lambda'' (H_{K(\tau)}(X_i)^\top \rho_K^{**}(\tau)) \right\| + o_p(N^{3c-1/2}) \\ &= O_p(N^{3c-1/2}). \end{aligned}$$

and, therefore

$$\begin{aligned}
& \widehat{UQPE}_{\text{RIF-NP}}(\tau) - UQPE(\tau) \\
&= \frac{1}{N} \cdot \sum_{i=1}^N (H_{K(\tau)}(X_i)^\top \cdot (\widehat{\rho}_K(\tau) - \widetilde{\rho}_K(\tau))) \cdot (H'_{K(\tau)}(X_i)^\top \cdot \rho_K(\tau)) \cdot \Lambda''(H_{K(\tau)}(X_i)^\top \rho_K^{**}(\tau)) \\
& \qquad \qquad \qquad + o_p(N^{3c-1/2}).
\end{aligned}$$

■

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