

# TAIL GINI FUNCTIONAL UNDER ASYMPTOTIC INDEPENDENCE

Zhaowen Wang

*Fudan University*

LiuJun Chen

*University of Science and Technology of China*

Deyuan Li

*Fudan University*

## Supplementary Material

In the supplementary material, we present the proofs of four auxiliary lemmas in Section S1, the proof of Proposition 1 in Section S2, an additional simulation study based on real value cases in SectionS3 and then show some additional figures for the application in Section S4.

### S1 Auxiliary Lemmas

To obtain the limit result in Proposition 1, we need Lemmas 1 and 2 below, which are important auxiliary results on the tail empirical processes and the tail empirical copula processes . They are analogous to Lemmas 1 and

2 in Cai and Musta (2020). The difference lies in the range of  $y$ . Here we take  $y \in [0, 1]$  instead of  $y \in [1/2, 2]$  in Cai and Musta (2020).

**Lemma 1.** (i) *The function  $y \mapsto \int_0^\infty \tau(x, y) dx^{-\gamma_1}$  is Lipschitz, that is, there exists  $C_1 > 0$  such that, for each  $y_1, y_2 \in [0, 1]$ ,*

$$\left| \int_0^\infty \tau(x, y_1) dx^{-\gamma_1} - \int_0^\infty \tau(x, y_2) dx^{-\gamma_1} \right| \leq C_1 |y_1 - y_2|.$$

(ii) *Let  $M_n = \sqrt{k} \left(\frac{n}{k}\right)^{-\frac{1}{2\eta} + \frac{1}{2}}$ . Assumptions 1, 2, 4 and 5 imply that*

$$\sup_{0 \leq y \leq 1} M_n \left| \int_0^\infty \tau(x, y) dx^{-\gamma_1} - \int_0^\infty \tau\left(s_{\frac{k}{n}}(x), y\right) dx^{-\gamma_1} \right| \rightarrow 0.$$

(iii) *Assumptions 3 and 4 imply that for  $\rho = 1, 2, 2 + \delta$ ,*

$$\sup_{0 \leq y \leq 1} \left| \int_0^\infty \tau_{\frac{k}{n}}(x, y) dx^{-\rho\gamma_1} - \int_0^\infty \tau(x, y) dx^{-\rho\gamma_1} \right| \rightarrow 0.$$

(iv) *Assumptions 3, 4 and 5 imply that*

$$\sup_{0 \leq y \leq 1} M_n \left| \int_0^\infty \tau_{\frac{k}{n}}\left(s_{\frac{k}{n}}(x), y\right) dx^{-\gamma_1} - \int_0^\infty \tau\left(s_{\frac{k}{n}}(x), y\right) dx^{-\gamma_1} \right| \rightarrow 0.$$

**Proof of Lemma 1.** (i) By the homogeneity of  $\tau(x, y)$ , we have that, for

$y_1, y_2 \in [0, 1]$ ,

$$\begin{aligned} & \left| \int_0^\infty \tau(x, y_1) dx^{-\gamma_1} - \int_0^\infty \tau(x, y_2) dx^{-\gamma_1} \right| \\ &= \left| \int_0^\infty y_1^{1/\eta} \tau\left(\frac{x}{y_1}, 1\right) dx^{-\gamma_1} - \int_0^\infty y_2^{1/\eta} \tau\left(\frac{x}{y_2}, 1\right) dx^{-\gamma_1} \right| \\ &= \left| y_1^{1/\eta - \gamma_1} \int_0^\infty \tau(x, 1) dx^{-\gamma_1} - y_2^{1/\eta - \gamma_1} \int_0^\infty \tau(x, 1) dx^{-\gamma_1} \right| \\ &\leq C_1 |y_1 - y_2|, \end{aligned}$$

where  $C_1 > 0$  is finite and the last inequality follows by  $0 < 1/\eta - \gamma_1 < 1$ .

(ii) For sufficiently small  $\epsilon > 0$ , let  $l_n = \left(\frac{k}{n}\right)^{1-\epsilon}$ . We write

$$\begin{aligned} & \sup_{0 \leq y \leq 1} M_n \left| \int_0^\infty \tau(x, y) dx^{-\gamma_1} - \int_0^\infty \tau\left(\frac{s_k}{n}(x), y\right) dx^{-\gamma_1} \right| \\ & \leq \sup_{0 \leq y \leq 1} M_n \left| \int_0^{l_n} \left[ \tau(x, y) - \tau\left(\frac{s_k}{n}(x), y\right) \right] dx^{-\gamma_1} \right| \\ & \quad + \sup_{0 \leq y \leq 1} M_n \left\{ \left| \int_{l_n}^\infty \tau(x, y) dx^{-\gamma_1} \right| + \left| \int_{l_n}^\infty \tau\left(\frac{s_k}{n}(x), y\right) dx^{-\gamma_1} \right| \right\}. \quad (\text{A1}) \end{aligned}$$

For the first term on the right-hand side of (A1), by the homogeneity and monotonicity of  $\tau(x, y)$ , we have that, for  $x_1, x_2 > 0, y \in [0, 1]$ ,

$$|\tau(x_1, y) - \tau(x_2, y)| \leq \left| \left(\frac{x_2}{x_1}\right)^{1/\eta} - 1 \right| \tau(x_1, y),$$

and hence

$$\begin{aligned} & \sup_{0 \leq y \leq 1} M_n \left| \int_0^{l_n} \left[ \tau(x, y) - \tau\left(\frac{s_k}{n}(x), y\right) \right] dx^{-\gamma_1} \right| \\ & \leq \sup_{0 \leq y \leq 1} M_n \left| \int_0^{l_n} \left| \left(\frac{s_k}{n}(x)}{x}\right)^{1/\eta} - 1 \right| \tau(x, y) dx^{-\gamma_1} \right|. \end{aligned}$$

Note that, for any  $\epsilon_0 > 0$ , for sufficiently large  $n$  and  $x < l_n$  (see Cai, 2012, p.85),

$$\left| \frac{s_k(x)/x - 1}{A_1(n/k)} - \frac{x^{-\rho_1} - 1}{\gamma_1 \rho_1} \right| \leq x^{-\rho_1} \max(x^{\epsilon_0}, x^{-\epsilon_0}).$$

This implies that for  $\epsilon_0 < -\rho_1(1 - \lambda)/\lambda$  and  $x < l_n$ ,

$$\left| \frac{s_k(x)}{x} - 1 \right| \leq |A_1(n/k)| \left\{ \left| \frac{x^{-\rho_1} - 1}{\gamma_1 \rho_1} \right| + x^{-\rho_1} \max(x^{\epsilon_0}, x^{-\epsilon_0}) \right\} = o(1).$$

By a Taylor expansion, we obtain

$$\left| \left( \frac{s_{\frac{k}{n}}(x)}{x} \right)^{1/\eta} - 1 \right| = |A_1(n/k)| \left\{ \left| \frac{x^{-\rho_1} - 1}{\gamma_1 \rho_1} \right| + x^{-\rho_1} \max(x^{\epsilon_0}, x^{-\epsilon_0}) \right\} \\ + o \left( |A_1(n/k)| \left\{ \left| \frac{x^{-\rho_1} - 1}{\gamma_1 \rho_1} \right| + x^{-\rho_1} \max(x^{\epsilon_0}, x^{-\epsilon_0}) \right\} \right).$$

Consequently,

$$\sup_{0 \leq y \leq 1} M_n \left| \int_0^{l_n} \left| \left( \frac{s_{\frac{k}{n}}(x)}{x} \right)^{1/\eta} - 1 \right| \tau(x, y) dx^{-\gamma_1} \right| \\ \leq C_2 \sup_{0 \leq y \leq 1} M_n |A_1(n/k)| \left| \int_0^{l_n} x^{-\rho_1} \max(x^{\epsilon_0}, x^{-\epsilon_0}) \tau(x, y) dx^{-\gamma_1} \right|, \quad (\text{A2})$$

where  $C_2 > 0$  is finite.

Furthermore, using the triangular inequality and Cauchy-Schwarz inequality, we have

$$\left| \int_0^{l_n} x^{-\rho_1} \max(x^{\epsilon_0}, x^{-\epsilon_0}) \tau(x, y) dx^{-\gamma_1} \right| \\ \leq \int_0^1 x^{-\rho_1 - \epsilon_0} \tau(x, y) dx^{-\gamma_1} + \left| \int_1^\infty \tau(x, y)^2 dx^{-\gamma_1} \right|^{1/2} \left| \int_1^{l_n} x^{-2\rho_1 + 2\epsilon_0} dx^{-\gamma_1} \right|^{1/2} \\ = O \left( l_n^{-\rho_1 + \epsilon_0 - \frac{\gamma_1}{2}} \right),$$

where the last equality follows from Assumption 2. Going back to (A2), we obtain

$$\sup_{0 \leq y \leq 1} M_n \left| \int_0^{l_n} \left| \left( \frac{s_{\frac{k}{n}}(x)}{x} \right)^{1/\eta} - 1 \right| \tau(x, y) dx^{-\gamma_1} \right| = O \left( \sqrt{k} \left( \frac{n}{k} \right)^{-\frac{1}{2\eta} + \frac{1}{2} - \frac{\gamma_1(1-\epsilon)}{2}} \right) \rightarrow 0,$$

because of Assumption 5.

Next, we deal with the second term in the right-hand side of (A1). By

Cauchy-Schwarz inequality and Assumption 2, we obtain

$$\begin{aligned} \left| \int_{l_n}^{\infty} \tau(x, y) dx^{-\gamma_1} \right| &\leq \gamma_1 \left( \int_{l_n}^{\infty} x^{-\gamma_1-1} dx \right)^{1/2} \left( \int_1^{\infty} \tau(x, y)^2 x^{-\gamma_1-1} dx \right)^{1/2} \\ &\leq C_3 l_n^{-\gamma_1/2} \end{aligned}$$

for some constant  $C_3 > 0$ . Moreover, by Assumption 5 and the fact that

$$M_n l_n^{\gamma_1/2} = \sqrt{k} \left( \frac{n}{k} \right)^{-\frac{1}{2\eta} + \frac{1}{2} - \frac{\gamma_1(1-\epsilon)}{2}},$$

it follows that

$$\sup_{0 \leq y \leq 1} M_n \left| \int_{l_n}^{\infty} \tau(x, y) dx^{-\gamma_1} \right| \rightarrow 0.$$

Again, the triangular inequality yields

$$\begin{aligned} &\left| \int_{l_n}^{\infty} \tau \left( s_{\frac{k}{n}}(x), y \right) dx^{-\gamma_1} \right| \\ &\leq \left| \int_{l_n}^{\infty} \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), y \right) dx^{-\gamma_1} \right| + \left| \int_{l_n}^{\infty} \left[ \tau \left( s_{\frac{k}{n}}(x), y \right) - \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), y \right) \right] dx^{-\gamma_1} \right| \\ &\leq \left| \int_{l_n}^{\infty} \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), y \right) dx^{-\gamma_1} \right| + \sup_{\substack{1 < x < \infty \\ 0 \leq y \leq 1}} \frac{\left| \tau_{\frac{k}{n}}(x, y) - \tau(x, y) \right|}{x^{\beta_2}} \int_{l_n}^{\infty} \left( s_{\frac{k}{n}}(x) \right)^{\beta_2} dx^{-\gamma_1}. \end{aligned}$$

Note that, by Assumption 4,

$$\sup_{\substack{1 < x < \infty \\ 0 \leq y \leq 1}} \frac{\left| \tau_{\frac{k}{n}}(x, y) - \tau(x, y) \right|}{x^{\beta_2}} = O \left( \left( \frac{n}{k} \right)^{-\xi} \right).$$

Then, by Jensen inequality and a change of variable, we obtain

$$\begin{aligned}
\int_1^\infty s_{\frac{k}{n}}(x)^{\beta_2} dx^{-\gamma_1} &= \int_1^\infty \left\{ \frac{n}{k} \mathbf{P}(X > Q_1(1 - k/n)x^{-\gamma_1}) \right\}^{\beta_2} dx^{-\gamma_1} \\
&= \left(\frac{n}{k}\right)^{\beta_2} \int_0^1 \{ \mathbf{P}(X > Q_1(1 - k/n)x) \}^{\beta_2} dx \\
&\leq \left(\frac{n}{k}\right)^{\beta_2} \left\{ \int_0^1 \mathbf{P}(X > Q_1(1 - k/n)x) dx \right\}^{\beta_2} \\
&= \left(\frac{n}{k}\right)^{\beta_2} \left\{ \frac{1}{Q_1(1 - k/n)} \int_0^{Q_1(1 - k/n)} \mathbf{P}(X > x) dx \right\}^{\beta_2} \\
&\leq \left(\frac{n}{k}\right)^{\beta_2(1-\gamma_1)} (\mathbb{E}[X])^{\beta_2}. \tag{A3}
\end{aligned}$$

Hence,  $\int_{l_n}^\infty s_{\frac{k}{n}}(x)^{\beta_2} dx^{-\gamma_1} \leq \int_1^\infty s_{\frac{k}{n}}(x)^{\beta_2} dx^{-\gamma_1} = O\left(\left(\frac{n}{k}\right)^{\beta_2(1-\gamma_1)}\right)$ . By Assumption 5, we have

$$\sup_{0 \leq y \leq 1} M_n \left| \int_{l_n}^\infty \left[ \tau\left(s_{\frac{k}{n}}(x), y\right) - \tau_{\frac{k}{n}}\left(s_{\frac{k}{n}}(x), y\right) \right] dx^{-\gamma_1} \right| = O\left(\sqrt{k} \left(\frac{n}{k}\right)^{-\frac{1}{2\eta} + \frac{1}{2} - \xi + \beta_2(1-\gamma_1)}\right) \rightarrow 0.$$

On the other hand, using the definition of  $s_{\frac{k}{n}}$ , we get

$$\begin{aligned}
&\left| \int_{l_n}^\infty \tau_{\frac{k}{n}}\left(s_{\frac{k}{n}}(x), y\right) dx^{-\gamma_1} \right| \\
&= \left| \int_{l_n}^\infty \left(\frac{n}{k}\right)^{1/\eta} \mathbf{P}\left[X > Q_1\left(1 - \frac{ks_{\frac{k}{n}}(x)}{n}\right), Y > Q_2\left(1 - \frac{ky}{n}\right)\right] dx^{-\gamma_1} \right| \\
&\leq \gamma_1 \frac{ky}{n} \left(\frac{n}{k}\right)^{1/\eta} l_n^{-\gamma_1}.
\end{aligned}$$

As a result, by Assumption 5 we obtain

$$\sup_{0 \leq y \leq 1} M_n \left| \int_{l_n}^\infty \tau_{\frac{k}{n}}\left(s_{\frac{k}{n}}(x), y\right) dx^{-\gamma_1} \right| \leq C\sqrt{k} \left(\frac{n}{k}\right)^{\frac{1}{2\eta} - \frac{1}{2} - (1-\epsilon)\gamma_1} \rightarrow 0.$$

(iii) We write

$$\begin{aligned}
& \sup_{0 \leq y \leq 1} \left| \int_0^\infty \tau_{\frac{k}{n}}(x, y) dx^{-\rho\gamma_1} - \int_0^\infty \tau(x, y) dx^{-\rho\gamma_1} \right| \\
& \leq \sup_{\substack{0 < x < \infty \\ 0 \leq y \leq 1}} \frac{\left| \tau_{\frac{k}{n}}(x, y) - \tau(x, y) \right|}{x^{\beta_1} \wedge x^{\beta_2}} \left| \int_0^\infty x^{\beta_1} \wedge x^{\beta_2} dx^{-\rho\gamma_1} \right| \\
& = O\left( \left( \frac{n}{k} \right)^{-\xi} \right) \left( \int_0^1 x^{\beta_1} dx^{-\rho\gamma_1} + \int_1^\infty x^{\beta_2} dx^{-\rho\gamma_1} \right) \\
& = o(1),
\end{aligned}$$

by Assumptions 3 and 4.

(iv) By Assumptions 3 and 4, we have

$$\begin{aligned}
& \sup_{0 \leq y \leq 1} M_n \left| \int_0^\infty \tau_{\frac{k}{n}}\left(s_{\frac{k}{n}}(x), y\right) - \tau\left(s_{\frac{k}{n}}(x), y\right) dx^{-\gamma_1} \right| \\
& \leq M_n \sup_{\substack{0 < x < \infty \\ 0 \leq y \leq 1}} \frac{\left| \tau_{\frac{k}{n}}(x, y) - \tau(x, y) \right|}{x^{\beta_1} \wedge x^{\beta_2}} \int_0^\infty \left( s_{\frac{k}{n}}(x)^{\beta_1} \wedge s_{\frac{k}{n}}(x)^{\beta_2} \right) dx^{-\gamma_1} \\
& = O\left( M_n \left( \frac{n}{k} \right)^{-\xi} \right) \int_0^\infty \left( s_{\frac{k}{n}}(x)^{\beta_1} \wedge s_{\frac{k}{n}}(x)^{\beta_2} \right) dx^{-\gamma_1}.
\end{aligned}$$

Next, we obtain an upper bound for the integral in the last equality.

Because  $s_{\frac{k}{n}}(x)$  is monotone and  $s_{\frac{k}{n}}(1) = 1$ , we get the following bound for

the integral from zero to one:

$$\int_0^1 s_{\frac{k}{n}}(x)^{\beta_1} dx^{-\gamma_1} < \int_{\mathbb{R}} \left( s_{\frac{k}{n}}(x)^{\beta_1} \wedge 1 \right) dx^{-\gamma_1},$$

which is shown to be  $O(1)$  in Cai, Einmahl, de Haan and Zhou (2015).

Recall that in (A3) we show

$$\int_1^\infty s_{\frac{k}{n}}(x)^{\beta_2} dx^{-\gamma_1} = O\left(\frac{n}{k}\right)^{\beta_2(1-\gamma_1)}.$$

Finally by Assumption 5, we get

$$O\left(M_n \left(\frac{n}{k}\right)^{-\xi+\beta_2(1-\gamma_1)}\right) = \sqrt{k} \left(\frac{n}{k}\right)^{-\frac{1}{2\eta}+\frac{1}{2}-\xi+\beta_2(1-\gamma_1)} \rightarrow 0.$$

□

**Lemma 2.** *Suppose Assumptions 2, 3 and 4 hold. For  $y \in [0, 1]$  and  $\rho \in \{1, 2, 2 + \delta\}$ , define*

$$A_n(y, \rho) = \left(\frac{n}{k}\right)^{1/\eta} \left(-\int_0^\infty \mathbf{1}_{\{1-F_1(X_1) < \frac{k}{n}x, 1-F_2(Y_1) < \frac{ky}{n}\}} dx^{-\gamma_1}\right)^\rho.$$

Then,

$$\mathbb{E}[A_n(y, \rho)] \rightarrow -\int_0^\infty \tau(x, y) dx^{-\rho\gamma_1}.$$

**Proof of Lemma 2.** Let  $U_i = 1 - F_1(X_i)$ ,  $V_i = 1 - F_2(Y_i)$ ,  $i = 1, \dots, n$ ,

then we can write the integral as

$$\int_0^\infty \mathbf{1}_{\{U_1 < \frac{k}{n}x, V_1 < \frac{ky}{n}\}} dx^{-\gamma_1} = -\mathbf{1}_{\{V_1 < \frac{ky}{n}\}} \left(U_1 \frac{n}{k}\right)^{-\gamma_1}.$$

By a change of variable, we obtain

$$\begin{aligned}
 \mathbb{E}[A_n(y, \rho)] &= \left(\frac{n}{k}\right)^{1/\eta} \mathbb{E} \left[ \mathbf{1}_{\{V_1 < \frac{ky}{n}\}} \left(\frac{n}{k}U_1\right)^{-\rho\gamma_1} \right] \\
 &= \left(\frac{n}{k}\right)^{1/\eta} \int_0^\infty \mathbf{P} \left( U_1 < \frac{k}{n}x^{-\frac{1}{\rho\gamma_1}}, V_1 < \frac{ky}{n} \right) dx \\
 &= - \left(\frac{n}{k}\right)^{1/\eta} \int_0^\infty \mathbf{P} \left( U_1 < \frac{k}{n}x, V_1 < \frac{ky}{n} \right) dx^{-\rho\gamma_1} \\
 &= - \int_0^\infty \tau_{\frac{k}{n}}(x, y) dx^{-\rho\gamma_1}.
 \end{aligned}$$

The statement follows from (iii) in Lemma 1.  $\square$

Recall  $s_{\frac{k}{n}}(x) = n\bar{F}_1(Q_1(1 - k/n)x^{-\gamma_1})/k, x \in (0, \infty)$ . In Lemma 3 below we study the processes

$$Z_{n,i}^*(y) = -\frac{1}{M_n} \int_0^\infty \mathbf{1}_{\{U_i < \frac{k}{n}s_{\frac{k}{n}}(x), V_i < \frac{ky}{n}\}} dx^{-\gamma_1}, i = 1, \dots, n.$$

**Lemma 3.** *Suppose that Assumptions 1 to 5 hold. Then as  $n \rightarrow \infty$ ,*

$$\left\{ \sum_{i=1}^n (Z_{n,i}^*(y) - \mathbb{E}[Z_{n,i}^*(y)]) \right\}_{y \in [0,1]} \xrightarrow{d} \{W(y)\}_{y \in [0,1]},$$

where  $W(\cdot)$  is a mean zero Gaussian process on  $[0, 1]$  with covariance structure

$$\mathbf{E}[W(y_1)W(y_2)] = - \int_0^\infty \tau(x, y_1 \wedge y_2) dx^{-2\gamma_1}, \quad y_1, y_2 \in [0, 1].$$

**Proof of Lemma 3.** Given that we have  $\lim_{n \rightarrow \infty} s_{\frac{k}{n}}(x) = x$  by the regular variation of  $1 - F_1$ . We shall study a simpler process obtained by replacing

$s_{\frac{k}{n}}(x)$  with  $x$  :

$$Z_{n,i}(y) = -\frac{S_n}{k} \int_0^\infty \mathbf{1}_{\{U_i < \frac{k}{n}x, V_i < \frac{k}{n}y\}} dx^{-\gamma_1}.$$

To prove Lemma 3 , it suffices to show that

$$\sup_{y \in [0,1]} n\mathbb{E} [|Z_{n,1}^*(y) - Z_{n,1}(y)|] \rightarrow 0, \quad (\text{A4})$$

and

$$\left\{ \sum_{i=1}^n (Z_{n,i}(y) - \mathbb{E}[Z_{n,i}(y)]) \right\}_{y \in [0,1]} \xrightarrow{d} \{W(y)\}_{y \in [0,1]}. \quad (\text{A5})$$

(A4) implies that

$$\sup_{y \in [0,1]} \sum_{i=1}^n (Z_{n,i}^*(y) - Z_{n,i}(y)) \xrightarrow{\mathbf{P}} 0$$

and

$$\sup_{y \in [0,1]} \sum_{i=1}^n (\mathbb{E}[Z_{n,i}^*(y)] - \mathbb{E}[Z_{n,i}(y)]) \xrightarrow{\mathbf{P}} 0.$$

*Step 1: Proof of (A4)*

Using the triangular inequality, we write

$$\begin{aligned} & n\mathbb{E}[|Z_{n,1}^*(y) - Z_{n,1}(y)|] \\ &= -\left(\frac{n}{k}\right)^{\frac{1}{2n}-\frac{1}{2}} \frac{n}{\sqrt{k}} \int_0^\infty \mathbf{P}\left(\frac{k}{n}(x \wedge s_{\frac{k}{n}}(x)) < U_1 < \frac{k}{n}(x \vee s_{\frac{k}{n}}(x)), V_1 < \frac{k}{n}y\right) dx^{-\gamma_1} \\ &= -M_n \int_0^\infty \left(\tau_{\frac{k}{n}}(x \vee s_{\frac{k}{n}}(x), y) - \tau_{\frac{k}{n}}(x \wedge s_{\frac{k}{n}}(x), y)\right) dx^{-\gamma_1} \\ &\leq -M_n \int_0^\infty \left|\tau(x, y) - \tau\left(s_{\frac{k}{n}}(x), y\right)\right| dx^{-\gamma_1} \\ &\quad - M_n \int_0^\infty \left|\tau_{\frac{k}{n}}(x, y) - \tau(x, y)\right| dx^{-\gamma_1} \\ &\quad - M_n \int_0^\infty \left|\tau_{\frac{k}{n}}\left(s_{\frac{k}{n}}(x), y\right) - \tau\left(s_{\frac{k}{n}}(x), y\right)\right| dx^{-\gamma_1}. \end{aligned}$$

All three terms on the right-hand side converge to zero by (ii) and (iii) in Lemma 1.

*Step 2: Proof of (A5)*

We aim to apply Theorem 2.11.9 in van der Vaart and Wellner (1996). In order to do this, we need to check the four conditions in that theorem are satisfied. Let  $(\mathcal{F}, \rho) = \{[0, 1], \rho(y_1, y_2) = |y_1 - y_2|\}$ , and  $\|Z\|_{\mathcal{F}} = \sup_{y \in \mathcal{F}} |Z(y)|$ .

(a) Fix  $\epsilon > 0$ . By the fact that  $\|Z_{n,1}\|_{\mathcal{F}} \leq Z_{n,1}(1)$ , we have that, with the notation  $\delta$  in Assumption 2,

$$\begin{aligned}
n\mathbb{E} \left[ \|Z_{n,1}\|_{\mathcal{F}} \mathbf{1}_{\{\|Z_{n,1}\|_{\mathcal{F}} > \epsilon\}} \right] &\leq n\mathbb{E} \left[ Z_{n,1}(1) \mathbf{1}_{\{Z_{n,1}(1) > \epsilon\}} \right] \\
&\leq \frac{n}{\epsilon^{1+\delta}} \mathbb{E} \left[ Z_{n,1}^{2+\delta}(1) \right] \\
&= \frac{1}{\epsilon^{1+\delta}} M_n^{-\delta} \mathbb{E} \left[ \left( \frac{n}{k} \right)^{1/\eta} \left( - \int_0^\infty \mathbf{1}_{\{U_i < \frac{k}{n}x, V_i < \frac{k}{n}\}} dx^{-\gamma_1} \right)^{2+\delta} \right] \\
&\rightarrow 0. \tag{A6}
\end{aligned}$$

The last convergence follows from  $M_n \rightarrow \infty$  and Lemma 2 .

(b) Take a positive sequence  $\delta_n \rightarrow 0$ . Then we have

$$\begin{aligned}
& \sup_{|y_1 - y_2| < \delta_n} \sum_{i=1}^n \mathbb{E} [(Z_{n,i}(y_1) - Z_{n,i}(y_2))^2] \\
&= \sup_{|y_1 - y_2| < \delta_n} \sum_{i=1}^n \left(\frac{n}{k}\right)^{\frac{1}{\eta}-1} \frac{1}{k} \mathbb{E} \left[ \left( \int_0^\infty \mathbf{1}_{\{U_i < \frac{k}{n}x, \frac{k}{n}y_2 < V_i < \frac{k}{n}y_1\}} dx^{-\gamma_1} \right)^2 \right] \\
&= \sup_{|y_1 - y_2| < \delta_n} \left(\frac{n}{k}\right)^{\frac{1}{\eta}} \mathbb{E} \left[ \mathbf{1}_{\{\frac{k}{n}y_1 < V_1 < \frac{k}{n}y_2\}} \left(\frac{n}{k}U_1\right)^{-2\gamma_1} \right].
\end{aligned}$$

Moreover, by triangular inequality and by (i) and (iii) in Lemma 1, we get

$$\begin{aligned}
& \left(\frac{n}{k}\right)^{\frac{1}{\eta}} \mathbb{E} \left[ \mathbf{1}_{\{\frac{k}{n}y < V_1 < \frac{k}{n}(y + \delta_n)\}} \left(\frac{n}{k}U_1\right)^{-2\gamma_1} \right] \\
&= - \left(\frac{n}{k}\right)^{\frac{1}{\eta}} \int_0^\infty \mathbf{P} \left( U_1 < \frac{k}{n}x, \frac{k}{n}y < V_1 < \frac{k}{n}(y + \delta_n) \right) dx^{-2\gamma_1} \\
&= \left| \int_0^\infty \tau_{\frac{k}{n}}(x, y + \delta_n) dx^{-2\gamma_1} - \int_0^\infty \tau_{\frac{k}{n}}(x, y) dx^{-2\gamma_1} \right| \rightarrow 0. \quad (\text{A7})
\end{aligned}$$

(c) Let  $N_{[\cdot]}(\epsilon, \mathcal{F}, L_2^n)$  be the minimal number of sets  $N_\epsilon$  in a partition

$[0, 1] = \cup_{j=1}^{N_\epsilon} I_{n,j}^\epsilon$  such that

$$\sum_{i=1}^n \mathbb{E} \left[ \sup_{y_1, y_2 \in I_{n,j}^\epsilon} |Z_{n,i}(y_1) - Z_{n,i}(y_2)|^2 \right] \leq \epsilon^2, \quad \forall j = 1, \dots, N_\epsilon.$$

Consider the partition given by  $I_{n,j}^\epsilon = [(j-1)\Delta_n, j\Delta_n]$ . Then,  $N_\epsilon = 1/\Delta_n$ .

We aim to find  $\Delta_n$  such that, for every sequence  $\delta_n \rightarrow 0$ , it follows that

$$\int_0^{\delta_n} \sqrt{\log N_{[\cdot]}(\epsilon, \mathcal{F}, L_2^n)} d\epsilon \rightarrow 0.$$

Notice that

$$n\mathbb{E} \left[ \sup_{y_1, y_2 \in I_{n,j}^\epsilon} |Z_{n,1}(y_1) - Z_{n,1}(y_2)|^2 \right] = \sup_{y_1, y_2 \in I_{n,j}^\epsilon} \left(\frac{n}{k}\right)^{\frac{1}{\eta}} \mathbb{E} \left[ \mathbf{1}_{\{\frac{k}{n}y_1 < V_1 < \frac{k}{n}y_2\}} \left(\frac{n}{k}U_1\right)^{-2\gamma_1} \right] =: B_n.$$

Let  $\bar{y}_1 = (j-1)\Delta_n$  and  $\bar{y}_2 = j\Delta_n$ . Next, we will derive two different upper bounds for  $B_n$ . Let  $q = (2 + \delta)/2$  and  $p$  such that  $1/p + 1/q = 1$ . By Hölder inequality, we obtain

$$\begin{aligned}
 B_n &\leq \left(\frac{n}{k}\right)^{\frac{1}{\eta}} \mathbb{E} \left[ \mathbf{1}_{\{\frac{k}{n}\bar{y}_1 < V_1 < \frac{k}{n}\bar{y}_2\}} \left( U_1 \frac{n}{k} \right)^{-2\gamma_1} \right] \\
 &\leq \left(\frac{n}{k}\right)^{\frac{1}{\eta}} \mathbb{E} \left[ \mathbf{1}_{\{\frac{k}{n}\bar{y}_1 < V_1 < \frac{k}{n}\bar{y}_2\}} \right]^{1/p} \mathbb{E} \left[ \mathbf{1}_{\{V_1 < \frac{k}{n}\bar{y}_2\}} \left( U_1 \frac{n}{k} \right)^{-2q\gamma_1} \right]^{1/q} \\
 &\leq \left(\frac{n}{k}\right)^{\frac{1}{\eta} - \frac{1}{p} - \frac{1}{nq}} |\bar{y}_1 - \bar{y}_2|^{\frac{1}{p}} \mathbb{E} [A_n(\bar{y}_2, 2q)] \\
 &= K_1 \left(\frac{n}{k}\right)^{\frac{1}{\eta} - \frac{1}{p} - \frac{1}{nq}} \Delta_n^{\frac{1}{p}},
 \end{aligned}$$

for some constant  $K_1 > 0$ , where the last equality is obtained by applying Lemma 2.

On the other hand, by (i) and (iii) in Lemma 1 and the triangular inequality, we get a second bound for  $B_n$  :

$$\begin{aligned}
 B_n &\leq -2 \int_0^\infty \left( \tau_{\frac{k}{n}}(x, \bar{y}_2) - \tau_{\frac{k}{n}}(x, \bar{y}_1) \right) dx^{-2\gamma_1} \\
 &= -2 \int_0^\infty \left( \tau(x, \bar{y}_2) - \tau(x, \bar{y}_1) \right) dx^{-2\gamma_1} \\
 &\quad - 2 \int_0^\infty \left( \tau_{\frac{k}{n}}(x, \bar{y}_2) - \tau(x, \bar{y}_2) \right) dx^{-2\gamma_1} \\
 &\quad - 2 \int_0^\infty \left( \tau(x, \bar{y}_1) - \tau_{\frac{k}{n}}(x, \bar{y}_1) \right) dx^{-2\gamma_1} \\
 &\leq K_2 \Delta_n + K_3 \left(\frac{k}{n}\right)^\xi
 \end{aligned}$$

for some positive constants  $K_2$  and  $K_3$ .

If  $\epsilon^2 < \left(\frac{k}{n}\right)^{\xi^*}$  for some  $\xi^* \in (0, \xi)$ , we use the first bound for  $B_n$ . By

choosing

$$\Delta_n = (K_1)^{-p} \left(\frac{n}{k}\right)^{-\frac{p}{\eta} + 1 + \frac{p}{\eta q}} \epsilon^{2p},$$

we get  $B_n \leq K_1 \left(\frac{n}{k}\right)^{\frac{1}{\eta} - \frac{1}{p} - \frac{1}{\eta q}} \Delta_n^{\frac{1}{p}} \leq \epsilon^2$ . Hence,

$$N_\epsilon \leq \frac{(K_1)^p}{\epsilon^{2p}} \left(\frac{n}{k}\right)^{\frac{p}{\eta} - 1 - \frac{p}{\eta q}}.$$

Otherwise, if  $\epsilon^2 > \left(\frac{k}{n}\right)^{\xi^*}$ , for sufficiently large  $n$ ,

$$K_3 \left(\frac{k}{n}\right)^\xi < \frac{1}{2} \left(\frac{k}{n}\right)^{\xi^*} < \frac{1}{2} \epsilon^2,$$

and we use the second bound for  $B_n$  with  $\Delta_n = \epsilon^2/(2K_2)$ , which means

$$B_n \leq K_2 \Delta_n + K_3 \left(\frac{k}{n}\right)^\xi \leq \epsilon^2$$

Hence, in this case,

$$N_\epsilon \leq \frac{2K_2}{\epsilon^2}.$$

Now, we distinguish between two cases. If  $\delta_n \sqrt{\log(n/k)} \rightarrow 0$ , using the inequality  $\sqrt{a+b} \leq \sqrt{a} + \sqrt{b}$ , for  $a, b > 0$  and the inequality  $\log(x) \leq x$  for large  $x$ , we get

$$\begin{aligned} \int_0^{\delta_n} \sqrt{\log N_{[\ ]}(\epsilon, \mathcal{F}, L_2^n)} d\epsilon &\leq \int_0^{\delta_n} \sqrt{\left(\frac{p}{\eta} - 1 - \frac{p}{\eta q}\right) \log(n/k) + 2p \log \epsilon^{-1} + \log(K_1)^p} d\epsilon \\ &\leq K_4 \left( \int_0^{\delta_n} \sqrt{\log(n/k)} d\epsilon + \int_0^{\delta_n} \sqrt{\epsilon^{-1}} d\epsilon \right), \end{aligned}$$

for some positive constants  $K_4$ , and the left-hand side converges to zero as

$\delta_n \rightarrow 0$ .

On the other hand, if  $\delta_n \sqrt{\log(n/k)} \not\rightarrow 0$ , we take  $\delta_n^* = (k/n)^{\xi^*}$ . Note that  $\delta_n^* \sqrt{\log(n/k)} \rightarrow 0$ . Hence, we write

$$\begin{aligned} \int_0^{\delta_n} \sqrt{\log N_{[\cdot]}(\epsilon, \mathcal{F}, L_2^n)} d\epsilon &= \int_0^{\delta_n^*} \sqrt{\log N_{[\cdot]}(\epsilon, \mathcal{F}, L_2^n)} d\epsilon + \int_{\delta_n^*}^{\delta_n} \sqrt{\log N_{[\cdot]}(\epsilon, \mathcal{F}, L_2^n)} d\epsilon \\ &\leq o(1) + \int_{\delta_n^*}^{\delta_n} \sqrt{\log(2K_2/\epsilon^2)} d\epsilon \\ &\leq o(1) + \sqrt{2} \int_0^{\delta_n} \sqrt{\epsilon^{-1}} d\epsilon \rightarrow 0. \end{aligned}$$

(d) We will show marginal convergence, that is, for each positive integer  $M$  and for each  $y_1, \dots, y_M \in [0, 1]$ , the random vector

$$\left( \sum_{i=1}^n (Z_{n,i}(y_1) - \mathbb{E}[Z_{n,i}(y_1)]), \dots, \sum_{i=1}^n (Z_{n,i}(y_M) - \mathbb{E}[Z_{n,i}(y_M)]) \right)$$

converges to a multivariate normal distribution. It suffices to show that, for each  $a_1, \dots, a_M \in \mathbb{R}$ ,

$$\sum_{j=1}^M a_j \left[ \sum_{i=1}^n (Z_{n,i}(y_j) - \mathbb{E}[Z_{n,i}(y_j)]) \right] =: \sum_{i=1}^n (N_{n,i} - \mathbb{E}[N_{n,i}])$$

converges to a normal distribution, where  $N_{n,i} = \sum_{j=1}^M a_j Z_{n,i}(y_j)$ . This will follow from the Lindeberg-Feller central limit theorem (see, e.g., Proposition 2.27 in van der Vaart (1998)), once we show that, for each  $\epsilon > 0$ ,

$$\sum_{i=1}^n \mathbb{E} [ |N_{n,i}|^2 \mathbf{1}_{\{|N_{n,i}| > \epsilon\}} ] \rightarrow 0 \tag{A8}$$

and

$$\sum_{i=1}^n \text{Var}(N_{n,i}) \rightarrow \sigma_N^2. \tag{A9}$$

We first proceed with (A8). Note that

$$\begin{aligned} \sum_{i=1}^n \mathbb{E} [ |N_{n,i}|^2 \mathbf{1}_{\{|N_{n,i}|>\epsilon\}} ] &= n \mathbb{E} [ |N_{n,1}|^2 \mathbf{1}_{\{|N_{n,1}|>\epsilon\}} ] \\ &\leq \frac{n \mathbb{E} [ |N_{n,1}|^{2+\delta} ]}{\epsilon^\delta} \leq K_5 n \sum_{j=1}^M |a_j|^{2+\delta} \frac{\mathbb{E} [ |Z_{n,1}(1)|^{2+\delta} ]}{\epsilon^\delta}, \end{aligned}$$

for some positive constants  $K_5$ , and converges to zero by (A6). For (A9),

we write

$$\begin{aligned} \sum_{i=1}^n \text{Var} (N_{n,i}) &= n \left\{ \mathbb{E} \left[ \left( \sum_{j=1}^M a_j Z_{n,1}(y_j) \right)^2 \right] - \left( \mathbb{E} \left[ \sum_{j=1}^M a_j Z_{n,1}(y_j) \right] \right)^2 \right\} \\ &= n \mathbb{E} \left[ \sum_{j=1}^M \sum_{k=1}^M a_j a_k Z_{n,1}(y_j) Z_{n,1}(y_k) \right] - \left( \sqrt{n} \sum_{j=1}^M a_j \mathbb{E} [Z_{n,1}(y_j)] \right)^2 \\ &= n \sum_{j=1}^M \sum_{k=1}^M a_j a_k \mathbb{E} [Z_{n,1}(y_j) Z_{n,1}(y_k)] + o(1), \end{aligned}$$

because it is easy to check that  $\sqrt{n} \mathbb{E} [Z_{n,1}(y_j)] \rightarrow 0$ , for  $j = 1, \dots, M$ .

Observe that

$$\begin{aligned} n \mathbb{E} [Z_{n,1}(y_j) Z_{n,1}(y_k)] &= \left( \frac{n}{k} \right)^{\frac{1}{n}} \mathbb{E} \left[ \left( \int_0^\infty \mathbf{1}_{\{U_1 < \frac{k}{n}x, V_1 < \frac{k}{n}(y_j \wedge y_k)\}} dx^{-\gamma_1} \right)^2 \right] \\ &= \mathbb{E} [A_n(y_j \wedge y_k, 1)]. \end{aligned}$$

Thus, by Lemma 2, it follows that (A9) holds with

$$\sigma_N^2 = - \sum_{j=1}^M \sum_{k=1}^M a_j a_k \int_0^\infty \tau(x, y_j \wedge y_k) dx^{-2\gamma_1}.$$

We have verified the four conditions required by Theorem 2.11.9 in van der Vaart and Wellner (1996), which means we have the conclusion that

$\sum_{i=1}^n (Z_{n,i} - \mathbb{E}[Z_{n,i}])$  converges weakly to a mean-zero Gaussian process  $W$ .

Now, we compute the covariance structure of the limit process. For each  $y_1, y_2 \in [0, 1]$ , by independence, we have

$$\begin{aligned} \mathbb{E}[W(y_1)W(y_2)] &= \lim_{n \rightarrow \infty} \text{Cov} \left( \sum_{i=1}^n Z_{n,i}(y_1), \sum_{i=1}^n Z_{n,i}(y_2) \right) \\ &= \lim_{n \rightarrow \infty} n \text{Cov}(Z_{n,1}(y_1), Z_{n,1}(y_2)) \\ &= \lim_{n \rightarrow \infty} (n\mathbb{E}[Z_{n,1}(y_1)Z_{n,1}(y_2)] - n\mathbb{E}[Z_{n,1}(y_1)]\mathbb{E}[Z_{n,1}(y_2)]) \\ &= - \int_0^\infty \tau(x, y_1 \wedge y_2) dx^{-2\gamma_1} \\ &= \int_0^\infty \tau \left( x^{-\frac{1}{2\gamma_1}}, y_1 \wedge y_2 \right) dx. \end{aligned}$$

□

In order to prove Proposition 2, we also need the Gaussian approximation to the tail empirical process for the marginal distribution of  $Y$ . Lemma 4 below is derived from Proposition 3.1 in Einmahl de Haan and Li (2006).

**Lemma 4.** *There exists a sequence of mean zero Gaussian processes  $\{\widetilde{W}_n(y)\}_{y \in [0,1]}$  with covariance structure*

$$\mathbb{E} \left[ \widetilde{W}_n(y_1) \widetilde{W}_n(y_2) \right] = y_1 \wedge y_2, \quad y_1, y_2 \in [0, 1],$$

*such that for any  $q \in [0, 1/2)$ , we have*

$$\sup_{y \in (0,1]} y^{-q} \left| \sqrt{n\alpha} \left( \frac{1}{n\alpha} \sum_{i=1}^n \mathbf{1}_{\{V_i < \alpha y\}} - y \right) - \widetilde{W}_n(y) \right| \xrightarrow{\mathbf{P}} 0.$$

## S2 Proof of Proposition 1

Let  $\hat{V}_i = 1 - F_{n2}(Y_i)$ , where  $F_{n2}(y) = \frac{1}{n+1} \sum_{i=1}^n \mathbf{1}_{\{Y_i \leq y\}}$  is the empirical distribution function of  $F_2$ . Recall that  $\alpha = k/n$ . Denote

$$\omega_n = 2\mathbb{E} \left( (X_1 - X_2) (V_2 - V_1) \mathbf{1}_{\{V_1 < \alpha, V_2 < \alpha\}} \right),$$

$$h(x_1, v_1, x_2, v_2) = 2(x_1 - x_2)(v_2 - v_1) \mathbf{1}_{\{V_1 < \alpha, V_2 < \alpha\}} - \omega_n,$$

$$h_1(x_1, v_1) = 2\mathbb{E} \left( (x_1 - X_2) (V_2 - v_1) \mathbf{1}_{\{V_1 < \alpha, V_2 < \alpha\}} \right) - \omega_n.$$

Therefore,  $\omega_n = \alpha^3 \text{TG}_{\frac{k}{n}}(X; Y)$  and

$$\begin{aligned} \hat{\theta}_{\frac{k}{n}} &= \frac{2n}{k^2(k-1)} \sum_{1 \leq i < j \leq n} \left[ \omega_n + h(X_i, \hat{V}_i, X_j, \hat{V}_j) \right] \\ &= \frac{n^2(n-1)}{k^2(k-1)} \omega_n + \frac{2n}{k^2(k-1)} \sum_{1 \leq i < j \leq n} h(X_i, \hat{V}_i, X_j, \hat{V}_j). \end{aligned}$$

By Hoeffding's Decomposition, we have that

$$\left( \frac{\sqrt{k}}{2n(n-1)} \sum_{1 \leq i < j \leq n} \frac{h(X_i, \hat{V}_i, X_j, \hat{V}_j)}{\alpha^3 Q_1(1-\alpha)} \right) = \sqrt{\frac{\alpha}{n}} \sum_{i=1}^n \frac{h_1(X_i, \hat{V}_i)}{2\alpha^3 Q_1(1-\alpha)} + o_{\mathbf{P}}(1).$$

Note that

$$\begin{aligned}
 h_1(x_1, v_1) &= -2x_1v_1I(v_1 < \alpha)\mathbf{P}(V_2 < \alpha) + 2x_1I(v_1 < \alpha)\mathbb{E}V_2I(V_2 < \alpha) \\
 &\quad + 2v_1I(v_1 < \alpha)\mathbb{E}X_2I(V_2 < \alpha) - 2I(v_1 < \alpha)\mathbb{E}X_2V_2I(V_2 < \alpha) - \omega_n \\
 &= 2\alpha(-x_1v_1I(v_1 < \alpha) + \mathbb{E}X_1V_1I(V_1 < \alpha)) \\
 &\quad + \alpha^2(x_1I(v_2 < \alpha) - \mathbb{E}X_1I(V_1 < \alpha)) \\
 &\quad + 2(v_1I(v_1 < \alpha) - \mathbb{E}V_1I(V_1 < \alpha))\mathbb{E}X_1I(V_1 < \alpha) \\
 &\quad - 2(I(v_1 < \alpha) - \alpha)\mathbb{E}X_1V_1I(V_1 < \alpha).
 \end{aligned}$$

Hence,

$$\begin{aligned}
 &\left(\frac{n}{k}\right)^{\frac{1}{2\eta}-\frac{1}{2}}\sqrt{\frac{\alpha}{n}}\sum_{i=1}^n\frac{h_1(X_i, \hat{V}_i)}{2\alpha^3Q_1(1-\alpha)} \\
 &= \left(\frac{n}{k}\right)^{\frac{1}{2\eta}-\frac{1}{2}}\sqrt{\frac{\alpha}{n}}\sum_{i=1}^n\left(\frac{-X_i\hat{V}_iI(\hat{V}_i < \alpha) + \mathbb{E}X_1V_1I(V_1 < \alpha)}{\alpha^2Q_1(1-\alpha)}\right) \\
 &\quad + \left(\frac{n}{k}\right)^{\frac{1}{2\eta}-\frac{1}{2}}\sqrt{\frac{\alpha}{n}}\sum_{i=1}^n\left(\frac{X_iI(\hat{V}_i < \alpha) - \mathbb{E}X_1I(V_1 < \alpha)}{2\alpha Q_1(1-\alpha)}\right) \\
 &\quad + \left(\frac{n}{k}\right)^{\frac{1}{2\eta}-\frac{1}{2}}\sqrt{\frac{\alpha}{n}}\sum_{i=1}^n\frac{(\hat{V}_iI(\hat{V}_i < \alpha) - \mathbb{E}V_1I(V_1 < \alpha))\mathbb{E}X_1I(V_1 < \alpha)}{\alpha^3Q_1(1-\alpha)} \\
 &\quad - \left(\frac{n}{k}\right)^{\frac{1}{2\eta}-\frac{1}{2}}\sqrt{\frac{\alpha}{n}}\sum_{i=1}^n\frac{(I(\hat{V}_i < \alpha) - \alpha)\mathbb{E}X_1V_1I(V_1 < \alpha)}{\alpha^3Q_1(1-\alpha)} \\
 &=: J_1 + J_2 + J_3 + J_4.
 \end{aligned}$$

Let  $e_n = \bar{F}_2(Y_{n-k,n})/\alpha$ . By Skorohod's representation and Lemma 3, there exists a sequence of mean zero Gaussian processes  $\{W_n(y)\}_{y \in [0,1]}$  with co-

variance structure

$$\mathbf{E} [W_n(y_1) W_n(y_2)] = - \int_0^\infty \tau(x, y_1 \wedge y_2) dx^{-2\gamma_1}, \quad y_1, y_2 \in [0, 1]$$

such that

$$\sup_{y \in [0,1]} \left| \sum_{i=1}^n (Z_{n,i}^*(y) - \mathbb{E} [Z_{n,i}^*(y)]) - W_n(y) \right| = o_{\mathbf{P}}(1).$$

For  $J_1$ , by Fubini's Theorem and a change of variables, we have that

$$\begin{aligned} J_1 &= \int_0^1 \sum_{i=1}^n (\mathbb{E} [Z_{n,i}^*(y)] - e_n^2 Z_{n,i}^*(e_n y)) dy \\ &= -e_n^2 \int_0^1 \left( \sum_{i=1}^n (Z_{n,i}^*(e_n y) - \mathbb{E} [Z_{n,i}^*(e_n y)]) - W_n(e_n y) \right) dy \\ &\quad - e_n^2 \int_0^1 \sum_{i=1}^n (\mathbb{E} [Z_{n,i}^*(e_n y) - Z_{n,i}^*(y)]) dy \\ &\quad - (e_n^2 - 1) \int_0^1 \sum_{i=1}^n \mathbb{E} [Z_{n,i}^*(y)] dy \\ &\quad - e_n^2 \int_0^1 W_n(e_n y) dy \\ &=: J_{11} + J_{12} + J_{13} + J_{14}. \end{aligned}$$

First, we show that  $J_{11} = o_{\mathbf{P}}(1)$ . Define  $Q_n(y) = \sum_{i=1}^n (Z_{n,i}^*(y) - \mathbb{E} [Z_{n,i}^*(y)]) - W_n(y)$ . By Lemma 4, we have  $\sqrt{k}(e_n - 1) = -\widetilde{W}_n(1) + o_{\mathbf{P}}(1)$ , and thus

$$\lim_{n \rightarrow \infty} \mathbf{P}(|e_n - 1| > k^{-1/4}) = 0.$$

Corollary 1.11 in Adler (1990) implies that as  $n \rightarrow \infty$ ,

$$\sup_{y \in (0,1], |e_n - 1| < k^{-1/4}} |Q_n(e_n y) - Q_n(y)| = o(1) \text{ a.s.},$$

which leads to

$$J_{11} = -e_n^2 \int_0^1 Q_n(e_n y) dy = o_{\mathbf{P}}(1).$$

Second, for  $J_{12}$ , using triangular inequality, we write

$$\begin{aligned} J_{12} &= -e_n^2 \int_0^1 n \mathbb{E}[|Z_{n,1}^*(e_n y) - Z_{n,1}^*(y)|] dy \\ &= e_n^2 \left(\frac{n}{k}\right)^{\frac{1}{2n}-\frac{1}{2}} \frac{n}{\sqrt{k}} \int_0^1 \int_0^\infty \left[ \mathbf{P}\left(U_1 < \frac{k}{n} s_{\frac{k}{n}}(x), V_1 < \frac{k}{n} e_n y\right) - \mathbf{P}\left(U_1 < \frac{k}{n} s_{\frac{k}{n}}(x), V_1 < \frac{k}{n} y\right) \right] dx^{-\gamma_1} dy \\ &= e_n^2 \int_0^1 M_n \int_0^\infty \left[ \tau_{\frac{k}{n}}\left(s_{\frac{k}{n}}(x), e_n y\right) - \tau_{\frac{k}{n}}\left(s_{\frac{k}{n}}(x), y\right) \right] dx^{-\gamma_1} dy \\ &\leq e_n^2 \int_0^1 M_n \int_0^\infty \left[ \tau_{\frac{k}{n}}\left(s_{\frac{k}{n}}(x), e_n y\right) - \tau\left(s_{\frac{k}{n}}(x), e_n y\right) \right] dx^{-\gamma_1} dy \\ &\quad - e_n^2 \int_0^1 M_n \int_0^\infty \left[ \tau_{\frac{k}{n}}\left(s_{\frac{k}{n}}(x), y\right) - \tau\left(s_{\frac{k}{n}}(x), y\right) \right] dx^{-\gamma_1} dy \\ &\quad + e_n^2 \int_0^1 M_n \int_0^\infty \left[ \tau\left(s_{\frac{k}{n}}(x), e_n y\right) - \tau(x, e_n y) \right] dx^{-\gamma_1} dy \\ &\quad - e_n^2 \int_0^1 M_n \int_0^\infty \left[ \tau\left(s_{\frac{k}{n}}(x), y\right) - \tau(x, y) \right] dx^{-\gamma_1} dy \\ &\quad + e_n^2 \int_0^1 M_n \int_0^\infty \left[ \tau(x, e_n y) - \tau(x, y) \right] dx^{-\gamma_1} dy \\ &=: J_{121} - J_{122} + J_{123} - J_{124} + J_{125}. \end{aligned}$$

We have  $J_{121} = o_{\mathbf{P}}(1)$ ,  $J_{122} = o_{\mathbf{P}}(1)$ ,  $J_{123} = o_{\mathbf{P}}(1)$ ,  $J_{124} = o_{\mathbf{P}}(1)$  by (iii) and

(iv) in Lemma 1. For  $J_{125}$ , by the homogeneity of function  $\tau$ , we have

$$J_{125} = M_n (e_n^{\frac{1}{n}-\gamma_1} - 1) e_n^2 \int_0^1 \int_0^\infty \tau(x, y) dx^{-\gamma_1} dy.$$

Note that

$$M_n (e_n^{\frac{1}{n}-\gamma_1} - 1) = \left(\frac{n}{k}\right)^{-\frac{1}{2n}+\frac{1}{2}} \sqrt{k} (e_n^{\frac{1}{n}-\gamma_1} - 1) \xrightarrow{\mathbf{P}} 0$$

because  $\sqrt{k}(e_n^{\frac{1}{n}-\gamma_1} - 1) = O_{\mathbf{P}}(1)$ . Consequently,  $J_{125} = o_{\mathbf{P}}(1)$  and hence  $J_{12} = o_{\mathbf{P}}(1)$ .

Third,  $\sqrt{k}(e_n^2 - 1) = O_{\mathbf{P}}(1)$  and

$$\int_0^1 \int_0^\infty \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), y \right) dx^{-\gamma_1} dy = \int_0^1 \int_0^\infty \tau(x, y) dx^{-\gamma_1} dy + o_{\mathbf{P}}(M_n^{-1})$$

lead to

$$J_{13} = \left( \frac{n}{k} \right)^{-\frac{1}{2n} + \frac{1}{2}} \sqrt{k}(e_n^2 - 1) \int_0^1 \int_0^\infty \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), y \right) dx^{-\gamma_1} dy \xrightarrow{\mathbf{P}} 0.$$

Fourth, again by Corollary 1.11 in Adler (1990), the continuity of  $W_n$  implies that as  $n \rightarrow \infty$ ,

$$\sup_{y \in (0,1], |e_n - 1| < k^{-1/4}} |W_n(e_n y) - W_n(y)| = o(1) \text{ a.s.},$$

which leads to that  $J_{14} = -\int_0^1 W_n(y) dy + o_{\mathbf{P}}(1)$ . Thus, we have  $J_1 = -\int_0^1 W_n(y) dy + o_{\mathbf{P}}(1)$ .

Similarly, for  $J_2$  we have that

$$\begin{aligned}
J_2 &= \frac{1}{2} \sum_{i=1}^n (\mathbb{E} [Z_{n,i}^*(1)] - e_n Z_{n,i}^*(e_n)) \\
&= -\frac{e_n}{2} \sum_{i=1}^n (Z_{n,i}^*(e_n) - \mathbb{E} [Z_{n,i}^*(e_n)]) - W_n(e_n) \\
&\quad - \frac{e_n}{2} \sum_{i=1}^n (\mathbb{E} [Z_{n,i}^*(e_n) - Z_{n,i}^*(1)]) \\
&\quad - \frac{e_n - 1}{2} \sum_{i=1}^n \mathbb{E} [Z_{n,i}^*(1)] \\
&\quad - \frac{e_n}{2} W_n(e_n) \\
&= J_{21} + J_{22} + J_{23} + J_{24}.
\end{aligned}$$

By  $e_n = o_{\mathbf{P}}(1)$  and Lemma 3, it follows that  $J_{21} = o_{\mathbf{P}}(1)$ ,  $J_{22} = o_{\mathbf{P}}(1)$ ,  $J_{23} = o_{\mathbf{P}}(1)$ ,  $J_{24} = -\frac{1}{2}W_n(1) + o_{\mathbf{P}}(1)$ , and thus  $J_2 = -\frac{1}{2}W_n(1) + o_{\mathbf{P}}(1)$ .

Next, we deal with  $J_3$ . Write

$$\begin{aligned}
J_3 &= S_n \int_0^\alpha \frac{1}{n} \sum_{i=1}^n \left( \frac{\mathbb{E}I(V_i < y) - I(V_i < e_n y)}{\alpha^2} \right) dy \times \frac{\mathbb{E}X_1 I(V_1 < \alpha)}{\alpha Q_1(1 - \alpha)} \\
&= \frac{M_n}{k} \int_0^1 \sum_{i=1}^n (I(V_i < e_n \alpha v) - \mathbb{E}I(V_1 < \alpha v)) dy \times \int_0^\infty \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), 1 \right) dx^{-\gamma_1} \\
&= \left(\frac{n}{k}\right)^{-\frac{1}{2n} + \frac{1}{2}} \int_0^1 \sqrt{n\alpha} \left( \frac{1}{n} \sum_{i=1}^n \frac{I(V_i < M_n \alpha y)}{\alpha} - e_n y \right) - \widetilde{W}_n(e_n y) dy \times \int_0^\infty \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), 1 \right) dx^{-\gamma_1} \\
&\quad - \left(\frac{n}{k}\right)^{-\frac{1}{2n} + \frac{1}{2}} \int_0^1 \sqrt{n\alpha} \left( \frac{1}{n} \sum_{i=1}^n \frac{I(V_i < \alpha y)}{\alpha} - y \right) - \widetilde{W}_n(y) dy \times \int_0^\infty \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), 1 \right) dx^{-\gamma_1} \\
&\quad + \left(\frac{n}{k}\right)^{-\frac{1}{2n} + \frac{1}{2}} \int_0^1 \sqrt{n\alpha} \left( \frac{1}{n} \sum_{i=1}^n \frac{I(V_i < \alpha y) - \mathbb{E}I(V_1 < \alpha y)}{\alpha} \right) - \widetilde{W}_n(y) dy \times \int_0^\infty \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), 1 \right) dx^{-\gamma_1} \\
&\quad + \left(\frac{n}{k}\right)^{-\frac{1}{2n} + \frac{1}{2}} \left[ \int_0^1 \left( \sqrt{n\alpha} (e_n - 1) y + \widetilde{W}_n(e_n y) - \widetilde{W}_n(y) \right) dy + \frac{1}{2} \widetilde{W}_n(1) \right] \times \int_0^\infty \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), 1 \right) dx^{-\gamma_1} \\
&\quad + M_n \int_0^\infty \left( \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), 1 \right) - \tau(x, 1) \right) dx^{-\gamma_1} \times \frac{1}{\sqrt{k}} \left( -\frac{1}{2} \widetilde{W}_n(1) + \int_0^1 \widetilde{W}_n(y) dy \right) \\
&\quad + \left(\frac{n}{k}\right)^{-\frac{1}{2n} + \frac{1}{2}} \left( -\frac{1}{2} \widetilde{W}_n(1) + \int_0^1 \widetilde{W}_n(y) dy \right) \times \int_0^\infty \tau(x, 1) dx^{-\gamma_1} \\
&=: J_{31} - J_{32} + J_{33} + J_{34} + J_{35} + J_{36}.
\end{aligned}$$

Lemma 4 and  $\int_0^\infty \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), 1 \right) dx^{-\gamma_1} \leq \infty$  imply that

$$J_{31} = o_{\mathbf{P}}(1), \quad J_{32} = o_{\mathbf{P}}(1), \quad J_{33} = o_{\mathbf{P}}(1).$$

Recall that  $\sqrt{n\alpha} (e_n - 1) = O_{\mathbf{P}}(1)$  and that  $\left(\frac{n}{k}\right)^{-\frac{1}{2n} + \frac{1}{2}} \rightarrow 0$ , so  $J_{34} = o_{\mathbf{P}}(1)$ .

By (ii) and (iv) in Lemma 1,  $J_{35} = o_{\mathbf{P}}(1)$  holds.  $J_{36} = o_{\mathbf{P}}(1)$  also holds because  $-\frac{1}{2} \widetilde{W}_n(1) + \int_0^1 \widetilde{W}_n(y) dy = O_{\mathbf{P}}(1)$  and  $\int_0^\infty \tau(x, 1) dx^{-\gamma_1} \leq \infty$ . Therefore,  $J_3 = o_{\mathbf{P}}(1)$ .

Similarly, for  $J_4$  we have

$$\begin{aligned}
 J_4 &= -S_n \left( \frac{1}{n\alpha} \sum_{i=1}^n I(V_i < e_n\alpha) - 1 \right) \times \frac{\mathbb{E}X_1 V_1 I(V_1 < \alpha)}{\alpha^2 Q_1(1-\alpha)} \\
 &= -\left(\frac{n}{k}\right)^{-\frac{1}{2\eta} + \frac{1}{2}} \left( \frac{\sqrt{n\alpha}}{n\alpha} \sum_{i=1}^n I(V_i < e_n\alpha) - 1 \right) \times \int_0^1 \int_0^\infty \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), y \right) dx^{-\gamma_1} dy \\
 &= -\left(\frac{n}{k}\right)^{-\frac{1}{2\eta} + \frac{1}{2}} \left[ \sqrt{n\alpha} \left( \frac{1}{n\alpha} \sum_{i=1}^n I(V_i < e_n\alpha) - e_n \right) - \widetilde{W}_n(e_n) \right] \times \int_0^1 \int_0^\infty \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), y \right) dx^{-\gamma_1} dy \\
 &\quad - \left(\frac{n}{k}\right)^{-\frac{1}{2\eta} + \frac{1}{2}} \left( \sqrt{n\alpha} (e_n - 1) + \widetilde{W}_n(1) \right) \times \int_0^1 \int_0^\infty \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), y \right) dx^{-\gamma_1} dy \\
 &\quad - \left(\frac{n}{k}\right)^{-\frac{1}{2\eta} + \frac{1}{2}} \left( \widetilde{W}_n(e_n) - \widetilde{W}_n(1) \right) \times \int_0^1 \int_0^\infty \tau_{\frac{k}{n}} \left( s_{\frac{k}{n}}(x), y \right) dx^{-\gamma_1} dy \\
 &= o_{\mathbf{P}}(1).
 \end{aligned}$$

By taking  $J_1, J_2, J_3$  and  $J_4$  together, we have

$$\begin{aligned}
 \sqrt{k} \frac{\phi_0}{4} \left(\frac{n}{k}\right)^{-\frac{1}{2\eta} + \frac{1}{2}} \left( \frac{\hat{\theta}_{k/n}}{\text{TG}_{k/n}(X; Y)} - 1 \right) &= \left(\frac{n}{k}\right)^{\frac{1}{2\eta} - \frac{1}{2}} \sqrt{\frac{\alpha}{n}} \sum_{i=1}^n \frac{h_1(X_i, \hat{V}_i)}{2\alpha^3 Q_1(1-\alpha)} \\
 &= -\int_0^1 W_n(y) dy - \frac{1}{2} W_n(1) + o_{\mathbf{P}}(1),
 \end{aligned}$$

and the proof is complete.  $\square$

### S3 Simulation

In this section, we present an additional simulation study for the real value case in the following Model 3: Model 3. Let  $Z_1, Z_2$ , and  $Z_3$  be independent Pareto random variables with parameters  $a_1, a_2$ , and  $a_1$ , respectively. Define

$$(X, Y) = (B - 2)(Z_1, Z_3) - (B + 1)(Z_2, Z_2),$$

Table S1: Parameters of Model 3 and the approximated true values of the tail Gini functional.

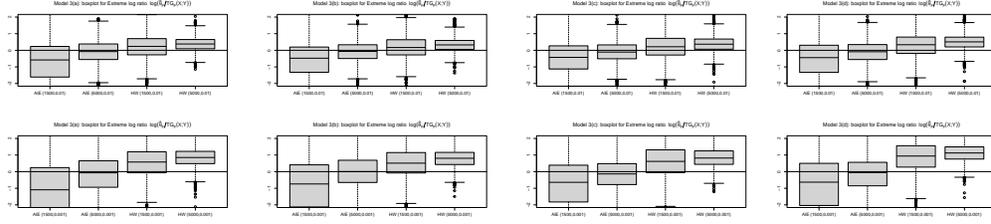
	$(a_1, a_2)$	$\gamma_1$	$\eta$	$-1/\eta + 1 + \gamma_1$	$p = 0.01$	$p = 0.001$
Model 3(a)	(0.35, 0.3)	0.35	6/7	0.183	2.3294	4.1145
Model 3(b)	(0.4, 0.35)	0.4	0.875	0.251	3.7148	7.2546
Model 3(c)	(0.6, 0.5)	0.6	5/6	0.1	11.5657	31.6759
Model 3(d)	(0.5, 0.4)	0.5	0.8	0.3	4.3407	8.2514

where  $B$  is a Bernoulli(1/2) random variable independent of  $Z_i$ 's. Here, both  $X$  and  $Y$  can take negative values. For this model, we have  $\gamma_1 = a_1$ ,  $\rho_1 = 1 - a_1/a_2$ ,  $\eta = a_2/a_1$ , and  $\tau(x, y) = 2^{a_1/a_2 - 1}(x \wedge y)^{a_1/a_2}$ . Here we can take  $\xi = 2a_1/a_2 - 1$ ,  $\delta = (2 - a_2^4)/a_2 - 1/a_1 - 2$ ,  $\beta_1 = a_1(2 - a_2^3)/a_2 - 1$ ,  $\beta_2 = (2a_1 - a_2^2)/(a_2(1 - a_1)) - 1/(1 - a_1)$ , and we note that Model 3 satisfies Assumptions 1 to 8. We consider four settings of  $(a_1, a_2)$ , see Table S1. Similar to Models 1 and 2, we calculate the true value  $\text{TG}_p(X; Y)$  at extreme level  $p = 0.01$  and  $0.001$  in Table S1.

Table S2 shows means and standard errors of the ratio  $\hat{\theta}_p/\text{TG}_p(X; Y)$  with sample sizes  $n = 1500$  and  $5000$  and number of replication  $m = 2000$ , comparing our proposed method (denoted by AIE) and the method in Hou and Wang (2021) (denoted by HW). We set  $\alpha = 0.09$ ,  $\alpha_1 = \alpha_2 = 0.05$ , following the main text. The boxplots of  $\log\left(\hat{\theta}_p/\text{TG}_p(X; Y)\right)$  are presented

Table S2: Means of the ratios of the proposed estimators for the tail Gini functional and the true values for  $n = 1500, 5000$  and  $p = 0.01, 0.001$  are reported with corresponding standard deviation given in the brackets.

		AIE		HW	
		$n = 1500$	$n = 5000$	$n = 1500$	$n = 5000$
Model 3(a)	$p = 0.01$	1.0520(1.5527)	1.1248(0.8205)	1.6293(1.6278)	1.6090(0.8035)
	$p = 0.001$	1.4935(3.9785)	1.4903(1.8521)	2.9316(4.4592)	2.7631(1.7631)
Model 3(b)	$p = 0.01$	1.0358(1.4254)	1.1281(0.8222)	1.5805(1.7725)	1.5327(0.7631)
	$p = 0.001$	1.8027(5.3756)	1.5776(1.7469)	3.0919(7.0181)	2.6237(1.6641)
Model 3(c)	$p = 0.01$	1.1102(1.7850)	1.1025(0.8593)	1.6622(2.2281)	1.6511(0.9825)
	$p = 0.001$	1.6663(3.9812)	1.3056(1.4575)	3.3475(5.4001)	2.8473(2.2396)
Model 3(d)	$p = 0.01$	1.0846(1.5885)	1.1086(0.4914)	1.7924(1.7869)	1.8311(0.9753)
	$p = 0.001$	1.8434(5.7193)	1.4566(1.9148)	4.4383(8.5167)	3.7037(2.7988)

Figure S1: Boxplots of log ratios with  $(n, p)$ .

in Figure S1. We can see that the proposed method has with sample size  $n = 5000$  performs the best among all scenarios. The QQ plots in Figure S2 indicate no big difference from a normal distribution when comparing the sample quantiles of log-ratios with the quantiles of the theoretical limit distribution.

## S4 Application

In this section, we assess the signs of  $\hat{\gamma}_1$  and  $\hat{\eta}$  for the 14 stocks that fail to reject asymptotic independence. We plot  $\hat{\gamma}$  and  $\hat{\eta}$  against different values of  $\alpha_1$  and  $\alpha_2$  in Figures S3 and S4, respectively. From Figures S3 and S4, we can see that  $\hat{\gamma}_1 > 0$  and  $\hat{\eta} \in (0.5, 1)$  for each pair of losses across the ranges of  $\alpha_1$  and  $\alpha_2$ .

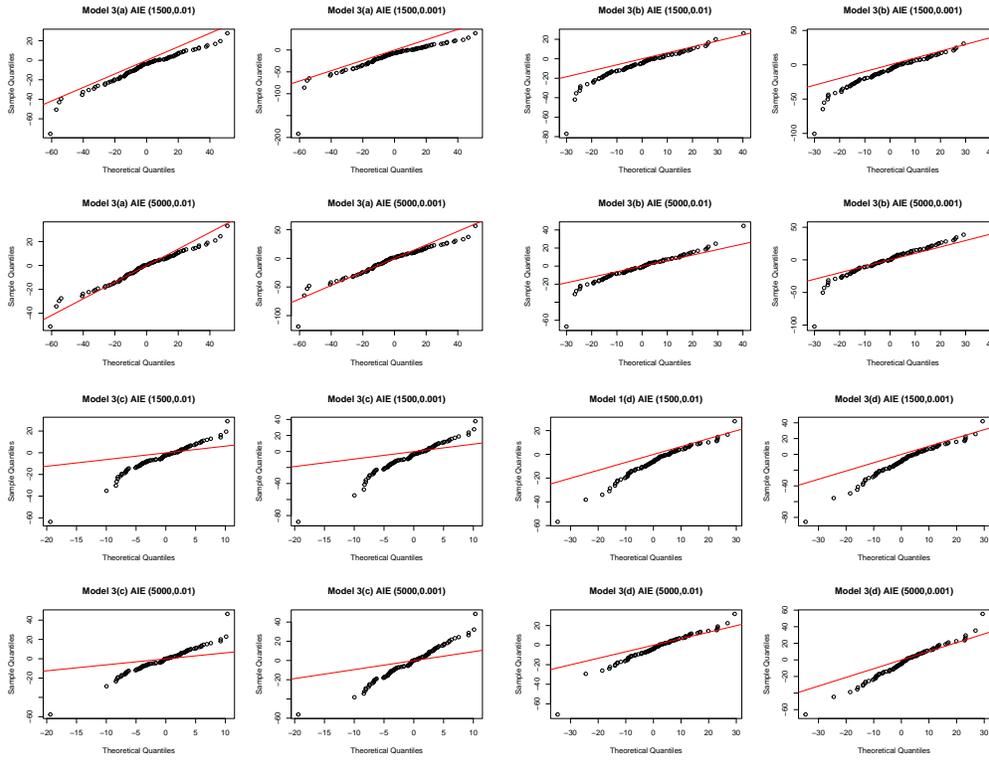


Figure S2: QQ plots of log ratios for AIE estimators for  $(n, p)$

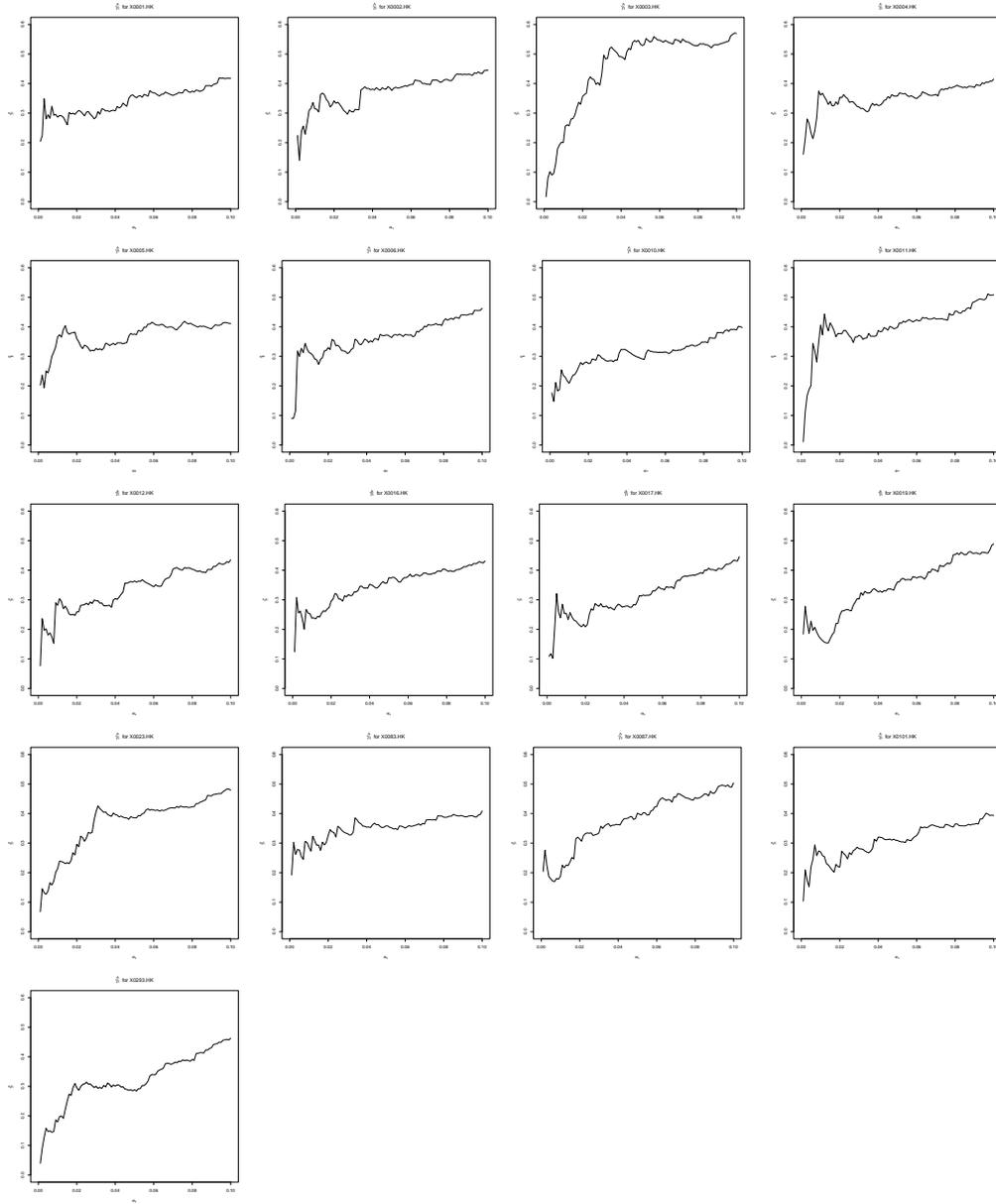
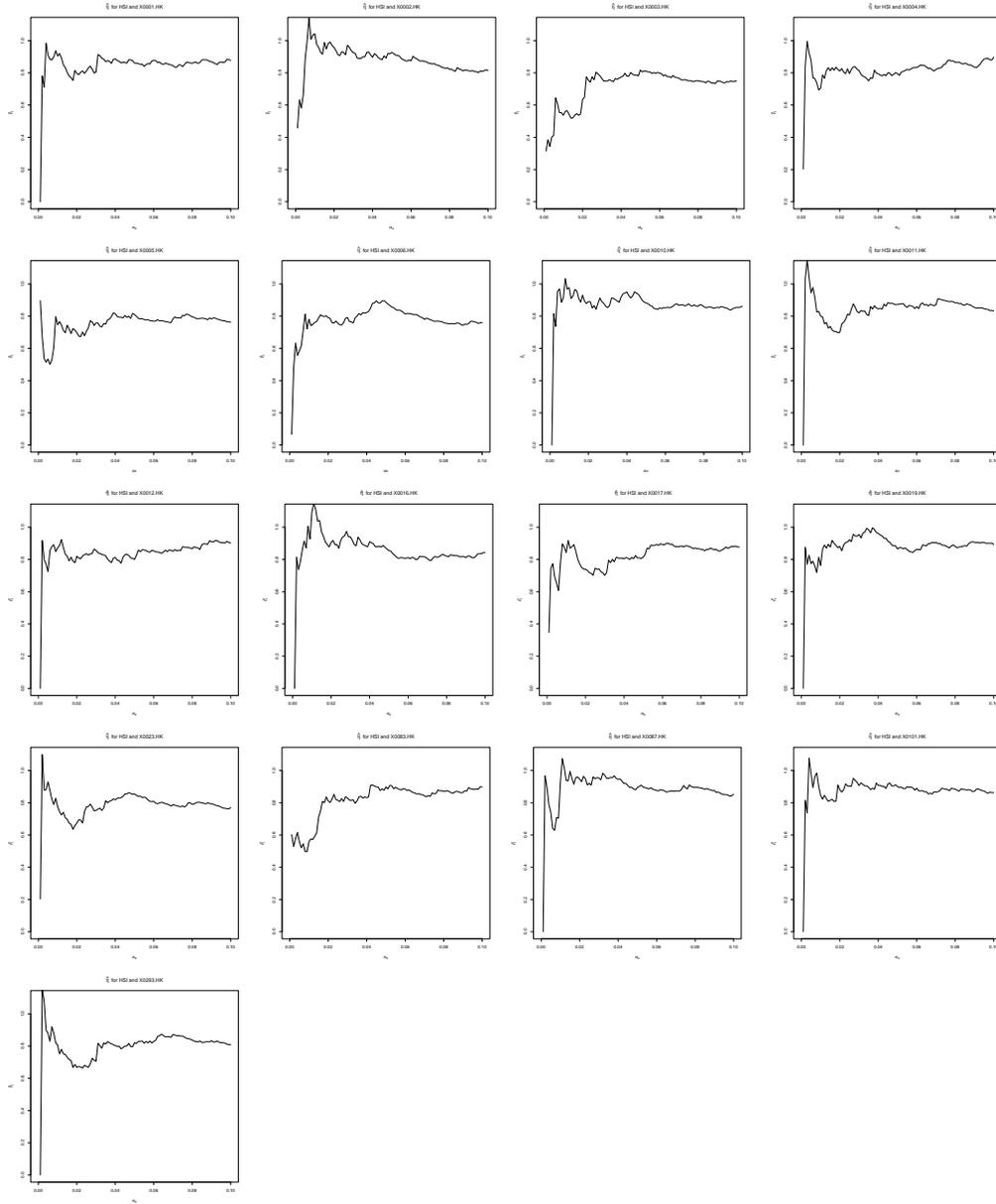


Figure S3: The Hill estimates of  $\gamma_1$ .

Figure S4: The estimates of  $\eta$ .

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