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Summary

The asymptotic consistency of the bootstrap approximation of the vector of the marginal generalized quantiles of U -statistic structure (multivariate U -quantiles for short) is established. The asymptotic accuracy of the bootstrap approximation is also obtained. Extensions to smooth functions of marginal generalized quantiles, are given and some specific examples, such as the vector of marginal sample quantiles, and the vector of marginal Hodges-Lehmann location estimators, are discussed.

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1 INTRODUCTION

In this paper we investigate Efron's bootstrap approximation for a wide class of multivariate generalized quantiles. We also look at the classical normal approximation for these multivariate statistics. Our results extend previous work by Choudhury and Serfling (1988) and Helmers, Janssen and Veravebeke (1992) for univariate U -quantiles' to the multivariate case. Let $X_1 = (X_{k1}, \dots, X_{k1}), \dots, X_N = (X_{1N}, \dots, X_{kN})$ be independent k -dimensional random vectors defined on a single probability space (Ω, \mathcal{A}, P) having common distribution function (*df*) F on \mathbb{R}^k . Let $h_1(x_1, \dots, x_m), \dots, h_q(x_1, \dots, x_m)$ be kernels of degree m (i.e., real-valued functions symmetric in its m arguments) and let

$$H_F(y) = P(h_j(X_{i1}, \dots, X_{im}) \leq Y_{ij}, i = 1, \dots, k, j = 1, \dots, q), \quad (1.1)$$

with $y = (y_{ij}, i = 1, \dots, k, j = 1, \dots, q) \in \mathbb{R}^{kq}$ denote this joint *df* of the kq random variables

$$h_j(X_{i1}, \dots, X_{im}), i = 1, \dots, k, j = 1, \dots, q. \quad (1.2)$$

In addition, let $H_{F_{i,j}}$ denote the marginal *df* of $h_j(X_{i1}, \dots, X_{im})$ and let, for $0 < p < 1$,

$$\xi_{ij}(p) = H_{F_{i,j}}^{-1}(p) = \inf\{x : H_{F_{i,j}}(x) \geq p\} \quad (1.3)$$

denote the corresponding p th marginal quantile. Define the associated empirical *df* of U -statistic structure

$$H_{N_{ij}}(y_{ij}) = \binom{N}{m}^{-1} \sum_{1 \leq \nu_1 < \dots < \nu_m \leq N} I(h_j(X_{i\nu_1}, \dots, X_{i\nu_m}) \leq y_{ij}) \quad (1.4)$$

for real y_{ij} and $N \geq m$, and let, for $0 < p < 1$

$$\hat{\xi}_{N_{ij}}(p) = H_{N_{ij}}^{-1}(p), \quad (1.5)$$

denote the corresponding p th empirical marginal quantile.

Statistics of the form (1.5) were considered by Hølmers, Janssen and Veraverbeke (1992) for the univariate case $k = q = 1$. Asymptotic consistency and the asymptotic accuracy of the bootstrap approximation for these univariate statistics (U -quantiles for short) was established. The present paper aims at extending these results to the multivariate case. Define *multivariate U -quantiles* by

$$(\hat{\xi}_{N_{11}}(p_{11}), \dots, \hat{\xi}_{N_{k1}}(p_{k1}), \dots, \hat{\xi}_{N_{1q}}(p_{1q}), \dots, \hat{\xi}_{N_{kq}}(p_{kq})) \quad (1.6)$$

where $0 < p_{ij} < 1$, $i = 1, \dots, k$, $j = 1, \dots, q$. In the special case $q = m = 1$ and $h_j(x) = x$, $j = 1, \dots, q$, (1.6) reduces to the k -vector of ordinary marginal quantiles studied by G.J. Babu and C.R. Rao (1988). These authors obtained asymptotic normality for this special case. In section 2 we extend their result to the more general class of multivariate U -quantiles of the form (1.6). We also obtain a Berry-Esseen bound for these statistics. In section 3 we derive the asymptotic consistency and establish the asymptotic accuracy of the bootstrap approximation for multivariate U -quantiles of type (1.6). Some useful extensions and specific examples are briefly discussed in section 4.

2 NORMAL APPROXIMATION

Let Σ denote the symmetric $kq \times kq$ -matrix with elements

$$\sigma_{ji,lr} = \text{cov}\{P(h_j(X_{i1}, \dots, X_{im}) \leq \xi_{ij}(p_{ij}) | X_{i1}), P(h_l(X_{r1}, \dots, X_{rm}) \leq \xi_{rl}(p_{ll}) | X_{r1})\} \quad (2.1)$$

with $i, r = 1, \dots, k$; $j, l = 1, \dots, q$. In addition, let

$$D_{H_F} = \text{diag}(h_{F_{11}}(\xi_{11}(p_{11})), \dots, h_{F_{k1}}(\xi_{k1}(p_{k1})), \dots, h_{F_{1q}}(\xi_{1q}(p_{1q})), \dots, h_{F_{kq}}(\xi_{kq}(p_{kq}))) \quad (2.2)$$

where $h_{F_{ij}}$ denotes the density of $H_{F_{ij}}$. Let $\xi = (\xi_{ij}(p_{ij}), i = 1, \dots, k, j = 1, \dots, q)$ and $\hat{\xi} = (\hat{\xi}_{ij}(p_{ij}), i = 1, \dots, k, j = 1, \dots, q)$. Clearly ξ denotes our parameter vector of interest and $\hat{\xi}$ its empirical counterpart (cf. (1.6)).

THEOREM 2.1. a. Let $H_{F_{ij}}$ be continuously differentiable with density $h_{F_{ij}}(\xi_{ij}(p_{ij})) > 0$. Then, as $N \rightarrow \infty$,

$$\sup_y |P(N^{\frac{1}{2}}(\hat{\xi} - \xi) \leq y) - \Phi(y; 0, m^2 D_{H_F}^{-\frac{1}{2}} \Sigma D_{H_F}^{-\frac{1}{2}})| \rightarrow 0 \quad (2.3)$$

where $\Phi(\cdot; 0, V)$ is the qk -variate normal distribution with mean vector 0 and covariance matrix V and $y = (y_{11}, \dots, y_{k1}, \dots, y_{1q}, \dots, y_{kq})'$.

b. In addition, suppose that $h_{F_{ij}}$ satisfies a Lipschitz condition of order $\geq \frac{1}{2}$ on a neighborhood of $\xi_{ij}(p_{ij})$, $i = 1, \dots, k$, $j = 1, \dots, q$ and Σ is positive definite, then, as $N \rightarrow \infty$,

$$\sup_y |P(N^{\frac{1}{2}}(\hat{\xi} - \xi) \leq y) - \Phi(y; 0, m^2 D_{H_F}^{-\frac{1}{2}} \Sigma D_{H_F}^{-\frac{1}{2}})| = O(N^{-\frac{1}{2}}). \quad (2.4)$$

PROOF. To begin with we remark that

$$\begin{aligned} P(N^{\frac{1}{2}}(\hat{\xi} - \xi) \leq y) &= P(N^{\frac{1}{2}}(\hat{\xi}_{ij}(p_{ij}) - \xi_{ij}(p_{ij})) \leq y_{ij}, \quad i = 1, \dots, k, \quad j = 1, \dots, q) \\ &= P(H_{N_{ij}}^{-1}(p_{ij}) \leq H_{F_{ij}}^{-1}(p_{ij}) + y_{ij} N^{-\frac{1}{2}}, \quad i = 1, \dots, k, \quad j = 1, \dots, q) \\ &= P(H_{N_{ij}}(H_{F_{ij}}^{-1}(p_{ij}) + y_{ij} N^{-\frac{1}{2}}) \geq p_{ij}, \quad i = 1, \dots, k, \quad j = 1, \dots, q) \end{aligned} \quad (2.5)$$

$$\begin{aligned}
&= P(N^{\frac{1}{2}}\{H_{N_{ij}}(H_{F_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}) - H_{F_{ij}}(H_{F_{ij}}^{-1}(p_{ij}) \\
&+ N^{-\frac{1}{2}}y_{ij})\} \geq N^{\frac{1}{2}}\{p_{ij} - H_{F_{ij}}(H_{F_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}})\}, i = 1, \dots, k, j = 1, \dots, q)
\end{aligned}$$

The smoothness assumption of $H_{F_{ij}}$ ensures that

$$\sqrt{N}\{p_{ij} - H_{F_{ij}}(H_{F_{ij}}^{-1}(p_{ij}) + N^{-\frac{1}{2}}y_{ij})\} \rightarrow -y_{ij}h_{F_{ij}}(\xi_{ij}(h_{ij})) \quad (2.6)$$

a.s. [P], for $i = 1, \dots, k, j = 1, \dots, q$. Next note that the random variable (r.v.) $T_{N_{ij}}(y_{ij})$ defined as

$$\sqrt{N}\{H_{N_{ij}}(H_{F_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}) - H_{F_{ij}}(H_{F_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}})\} \quad (2.7)$$

is a normalized U -statistic of degree m with bounded kernel, depending on n , of the form

$$h_{N_{ij}}(x_1, \dots, x_m; y_{ij}) = I\{h_j(x_1, \dots, x_m) \leq \xi_{ij}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}\} - \quad (2.8)$$

$$P(h_j(X_{i1}, \dots, X_{im}) \leq \xi_{ij}(p_{ij}) + y_{ij}N^{-\frac{1}{2}})$$

with $(x_1, \dots, x_m) \in \mathbb{R}^m$, for $i = 1, \dots, k, j = 1, \dots, q$. At this point we invoke an easy modification of the Theorem on p. 188 of Serfling (1980) to find that for $i = 1, \dots, k, j = 1, \dots, q$

$$E\{T_{N_{ij}}(y_{ij}) - \sum_{s=1}^N E(T_{N_{ij}}(y_{ij})|X_{is})\}^2 = O(N^{-1}). \quad (2.9)$$

In view of (2.5) - (2.9) and Chebychev's inequality it now clearly suffices to check that the kq -vector given by

$$\sum_{s=1}^N E(T_{N_{ij}}(y_{ij})|X_{is}), \quad i = 1, \dots, k, \quad j = 1, \dots, q \quad (2.10)$$

converges in distribution to $\Phi(\cdot; 0, \Sigma)$, as $n \leftarrow \infty$, with Σ as in (2.1). But this is an easy matter, because the random vector (2.10) is a normalized sum of i.i.d. random summands, with zero mean and covariance matrix V_N . Clearly

$$E(T_{N_{ij}}(y_{ij})|X_{is}) = \quad (2.11)$$

$$\begin{aligned}
&= \frac{m}{\sqrt{N}} \sum_{s=1}^N \{P(h_j(X_{is}, X_{i\nu_2}, \dots, X_{i\nu_m}) \leq \xi_{ij}(p_{ij}) + \\
&+ y_{ij}N^{-\frac{1}{2}}|X_{is}) - P(h_j(X_{i1}, \dots, X_{im}) \leq \xi_{ij}(p_{ij}) + \\
&+ y_{ij}N^{-\frac{1}{2}})\}, \quad i = 1, \dots, k, \quad j = 1, \dots, q,
\end{aligned}$$

where $1 \leq \nu_2 < \dots < \nu_m \leq N$ can be chosen arbitrary, provided $\nu_l \neq s, l = 2, \dots, m$. The $kq \times kq$ matrix V_N is precisely the covariance matrix of the kq -vector (2.11). It remains to show that V_N approaches Σ , as $N \rightarrow \infty$. The simple relation

$$\sigma^2 \left\{ \sum_{s=1}^N E((T_{N_{ij}}(Y_{ij}) - T_{N_{ij}}(0))|X_{is}) \right\} \leq m^2 \sigma^2 \{P(h_j(X_{i1}, \dots, X_{im}) \in (\xi_{ij}(p_{ij}), \quad (2.12)$$

$$, \xi_{ij}(p_{ij}) + y_{ij}N^{-\frac{1}{2}})|X_{i1})\} = O(N^{-1}), \quad \text{as } N \rightarrow \infty,$$

can be used. Here we have employed the mean value theorem (applied to $H_{F_{ij}}$ on a neighborhood of $\xi_{ij}(p_{ij})$) and a well-known property of conditional moments. Since the kq -vector given by

$$\sum_{s=1}^N E(T_{N_{ij}}(0)|X_{is}), \quad i = 1, \dots, k, \quad j = 1, \dots, q \quad (2.13)$$

has covariance matrix Σ (cf. (2.1)) our proof of relation (2.3) is now completed.

It remains to establish the Berry-Esseen bound (2.4). To do this we apply Theorem 1.16 of Götze (1987) to the kq -vector (cf. (2.7)) of U -statistic type

$$T_{N_{ij}}(y_{ij}), \quad i = 1, \dots, k, \quad j = 1, \dots, q. \quad (2.14)$$

The conditions of Götze's theorem are easily verified, since by assumption Σ is positive definite and the kernel functions $h_{N_{ij}}$ (cf. (2.8)) are all bounded by 1. In addition, relation (2.6) is now replaced by the stronger assertion that

$$\sqrt{N}\{p_{ij} - H_{F_{ij}}(H_{F_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}) + y_{ij}h_{F_{ij}}(\xi_{ij}(p_{ij}))\} = O(N^{-\frac{1}{2}}) \quad (2.15)$$

as $N \rightarrow \infty$. For this we use the Lipschitz condition on $h_{F_{ij}}$. This completes the proof of (2.4) and the theorem is proved. \square

Relation (2.3) extends related results of Choudhury and Serfling (1988) and Babu and Rao (1988) for the univariate case $k = q = 1$ respectively the case of ordinary marginal quantiles ($q = m = 1$, $h_1(x) = x$) to a considerably more general class of statistics. Relation (2.4) supplements all this with a Berry-Esseen bound. We note in passing that the strong consistency of multivariate U -quantiles $\hat{\xi}$ in estimating the parameter of interest ξ follows directly from Corollary 3.2 of Helmers, Janssen, Serfling (1988), provided ξ is uniquely determined.

In applications one often wishes to establish a confidence region for ξ and a studentized version of (2.3) is required, i.e. a consistent estimator of the covariance matrix in (2.3) is needed. An alternative approach is to employ bootstrap methods for the construction of a confidence region for ξ . In section 3 we establish a bootstrap analog of (2.3) under a slightly more stringent smoothness condition on H_F . With the aid of this result various bootstrap based confidence regions for ξ can easily be constructed.

3 BOOTSTRAP APPROXIMATION

Let \hat{F}_N denote the k -variate empirical df based on X_1, \dots, X_N . Define

$$H_{N_{ij}}^*(y_{ij}) = \binom{N}{m}^{-1} \sum_{1 \leq \nu_1 < \dots < \nu_k \leq N} \dots \sum I(h_j(X_{i\nu_1}^*, \dots, X_{i\nu_m}^*) \leq y_{ij}) \quad (3.1)$$

with $y_{ij} \in \mathbb{R}$, the marginal empirical df of U -statistic structure based on the (marginal) bootstrap sample $X_{i1}^*, \dots, X_{iN}^*$, i.e. the i -th component of X_1^*, \dots, X_N^* . Here and elsewhere X_1^*, \dots, X_N^* denotes a random sample drawn with replacement from \hat{F}_N , conditionally given X_1, \dots, X_N . Define $\hat{\xi}_{ij}^*(p) = H_{N_{ij}}^{*-1}(p)$, $0 < p < 1$, with $H_{N_{ij}}^*$ as in (3.1). Let P_N^* denote probability corresponding to \hat{F}_N .

THEOREM 3.1. a. Let $H_{F_{ij}}$ be continuously differentiable (with density $h_{F_{ij}}$) on a neighborhood of $\xi_{p_{ij}}$ with $h_{F_{ij}}(\xi_{ij}(p_{ij})) > 0$. Then, for almost every sample sequence X_1, X_2, \dots ,

$$\sup_y |P_N^*(\sqrt{N}(\hat{\xi}^* - \xi) \leq y) - \Phi(y; 0, m^2 D_{H_F}^{-\frac{1}{2}} \Sigma D_{H_F}^{-\frac{1}{2}})| \rightarrow 0, \text{ as } N \rightarrow \infty. \quad (3.2)$$

b. In addition, if $h_{F_{ij}}$ satisfies a Lipschitz condition of order $\geq \frac{1}{2}$ on a neighborhood of $\xi_{ij}(p_{ij})$, $i = 1, \dots, k$, $j = 1, \dots, q$ and Σ is positive definite, then

$$\sup_y |P_N^*(\sqrt{N}(\hat{\xi}^* - \hat{\xi}) \leq y) - P(\sqrt{N}(\hat{\xi} - \xi) \leq y)| = O(N^{-\frac{1}{4}}(\ln N)^{\frac{3}{4}}) \quad (3.3)$$

a.s. [P], as $N \rightarrow \infty$.

PROOF. Similarly as in the proof of Theorem 2.1 of Helmers, Janssen, Veraverbeke (1992) we write

$$P_N^*(\sqrt{N}(\hat{\xi}^* - \hat{\xi}) \leq y) = P_N^*(W_{N_{ij}}^*(y_{ij}) \geq -D_{N_{ij}}, i = 1, \dots, k, \dots, j = 1, \dots, q) \quad (3.4)$$

where

$$W_{N_{ij}}^*(y_{ij}) = \sqrt{N}\{H_{N_{ij}}^*(H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}) - \bar{H}_{N_{ij}}(H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}})\} \quad (3.5)$$

and

$$D_{N_{ij}} = \sqrt{N}\{\bar{H}_{N_{ij}}(H_{N_{ij}}^{-1}(p_{ij})) + y_{ij}N^{-\frac{1}{2}} - p_{ij}\} \quad (3.6)$$

with

$$\bar{H}_{N_{ij}}(y_{ij}) = N^{-m} \sum_{\nu_1=1}^N \dots \sum_{\nu_m=1}^N I(h_j(X_{i\nu_1}, \dots, X_{i\nu_m}) \leq y_{ij}) \quad (3.7)$$

for $i = 1, \dots, k, j = 1, \dots, q$. As in Helmers, Janssen, Veraverbeke (1992) we obtain that

$$D_{N_{ij}} \rightarrow y_{ij} h_{F_{ij}}(\xi_{ij}(p_{ij})). \quad \text{a.s. [P]}, \quad (3.8)$$

as $N \rightarrow \infty, i = 1, \dots, k, j = 1, \dots, q$.

To proceed we deal with the random variables $W_{N_{ij}}^*(y_{ij})$ defined in (3.5). Note that

$$\begin{aligned} W_{N_{ij}}^*(y_{ij}) &= \sqrt{N} \binom{N}{m}^{-1} \sum_{\nu_1 < \dots < \nu_m} I\{h_j(X_{i\nu_1}^*, \dots, X_{i\nu_m}^*) \leq \\ &\leq H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}\} - N^{-m} \sum_{s_1} \dots \sum_{s_m} I\{h_j(X_{is_1}, \dots, X_{is_m}) \leq \\ &\leq H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}\}, \quad j = 1, \dots, k, \quad j = 1, \dots, q \end{aligned} \quad (3.9)$$

is of U -statistic structure, with kernel

$$\begin{aligned} g_{N_{ij}}^*(x_1, \dots, x_m; y_{ij}) &= I\{h_j(x_1, \dots, x_m) \leq H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}\} \\ &- \frac{1}{N^m} \sum_{s_1} \dots \sum_{s_m} I\{h_j(X_{is_1}, \dots, X_{is_m}) \leq H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}\} \end{aligned} \quad (3.10)$$

for all $(x_1, \dots, x_m) \in \mathbb{R}^m$. The next step is to check that an order bound similar to (2.11), holds true here too. Because the $g_{N_{ij}}^*$'s are bounded by 1 in absolute value we indeed have that, for each $n \geq 2$,

$$E_N^*(T_{N_{ij}}^*(y_{ij}) - \sum_{s=1}^N E_N^*(T_{N_{ij}}^*(y_{ij}) | X_{is}^*))^{2r} = O(N^{-r}) \quad (3.11)$$

a.s. [P], as $N \rightarrow \infty$. Here $T_{N_{ij}}^*(y_{ij})$ is defined by (2.7) with X_{ij} replaced by X_{ij}^* , $H_{F_{ij}}$ by $H_{N_{ij}}$ and $H_{N_{ij}}$ by $H_{N_{ij}}^*$.

Similarly as in the proof of Theorem 2.1, relation (2.3), our problem reduces to one of proving the following result:

$$P_N^* \left(\sum_{s=1}^N \frac{m}{\sqrt{N}} (P_N^*(h_j(X_{is}^*, X_{i\nu_1}^*, \dots, X_{i\nu_{m-1}}^*) \leq \right) \leq \quad (3.12)$$

$$\begin{aligned}
& H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}|X_{is}^* - P_N^*(h_j(X_{i1}^*, \dots, X_{im}^*) \leq \\
& H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}) \leq z_{ij}, \quad i = 1, \dots, k, \quad j = 1, \dots, q) - \\
& - \Phi(z; 0, N \text{var}_N^* \{E_N^*(T_N^*(y)|X_1^*)\}) \rightarrow 0
\end{aligned}$$

a.s. [P], as $N \rightarrow \infty$, where we have used the fact that

$$\begin{aligned}
& \sum_{s=1}^N E_N^*(T_{N_{ij}}^*(y_{ij})|X_{is}^*) = \tag{3.13} \\
& = \sum_{s=1}^N (\sqrt{N} \binom{N}{m})^{-1} \sum_{\nu_1 < \dots < \nu_m} \dots \sum \\
& E_N^* (I\{h_j(X_{i\nu_1}^*, \dots, X_{i\nu_m}^*) \leq H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}\} - \\
& - N^{-m} \sum_{s_1} \dots \sum_{s_m} I\{h_j(X_{is_1}, \dots, X_{is_m}) \leq H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}\} | X_{is}^*) \\
& = \frac{m}{\sqrt{N}} \sum_{s=1}^N (P_N^*(h_j(X_{is}^*, X_{i\nu_2}^*, \dots, X_{i\nu_m}^*) \leq H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}} | X_{is}^*) \\
& - P_N^*(h_j(X_{i1}^*, \dots, X_{im}^*) \leq H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}} | X_{is}^*))
\end{aligned}$$

where $s \notin \{\nu_2, \dots, \nu_m\}$ and $\nu_2 < \dots < \nu_m$ in the next to last line. To proceed we note that (3.13) in turn is equal to

$$\begin{aligned}
& \frac{m}{\sqrt{N}} \sum_{s=1}^N N^{-m+1} \sum_{s_1} \dots \sum_{s_{m-1}} (I\{h_j(X_{is}^*, X_{is_1}, \dots, X_{is_{m-1}}) \\
& \leq H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}\} - \frac{1}{N} \sum_{l=1}^N I\{(h_j(X_{il}, X_{is_1}, \dots, X_{is_{m-1}}) \leq H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}\}) \tag{3.14}
\end{aligned}$$

Also note that the expression within curly brackets appearing in the Var_N^* matrix in (3.12) is nothing but the kq -vector.

$$E_N^*(T_N^*(y)|X_1^*) = (E_N^*(T_{N_{ij}}^*(y_{ij})|X_{i1}^*), \quad i = 1, \dots, k, \quad j = 1, \dots, q).$$

Clearly (3.12) is true, since $E^*(T_N^*(y)|X_s^*)$ is a sum of i.i.d. random vectors (conditionally given X_1, \dots, X_N). It remains, however, to investigate the covariance matrix of $E_N^*(T_N^*(y)|X_1^*)$, conditionally given X_1, \dots, X_N . To do this, we shall first check that

$$N \text{var}_N^* \{E_N^*(T_{N_{ij}}^*(y_{ij})|X_s^*) - E_N^*(T_{N_{ij}}^*(y_{ij})|X_{i1}^*)\} \tag{3.15}$$

is sufficiently small. In fact, we have that

$$\begin{aligned}
& N \text{var}_N^* \{E_N^*(T_{N_{ij}}^*(y_{ij})|X_s^*) - E_N^*(T_{N_{ij}}^*(y_{ij})|X_{i1}^*) - \\
& - \sqrt{N}(H_{F_{ij}}^{-1}(p_{ij}) - H_{N_{ij}}^{-1}(p_{ij}))\} \leq m^2 E_N^*(P_N^*(h_j(X_{i1}^*, \dots, X_{im}^*) \leq H_{N_{ij}}^{-1}(p_{ij})) | X_{ij}^*) \leq m^2 E_N^*(P_N^*(h_j(X_{i1}^*, \dots, X_{im}^*) \leq H_{N_{ij}}^{-1}(p_{ij})) | X_{ij}^*) \tag{3.16}
\end{aligned}$$

$$\begin{aligned}
& (H_{N_{ij}}^{-1}(p_{ij}), H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}|X_{i_s}^*)^2 = \\
& = m^2 \cdot N^{-1} \sum_{\nu_1} (N^{-m+1} \sum_{\nu_2} \dots \sum_{\nu_m} I\{h_j(X_{i\nu_1}, \dots, X_{i\nu_m}) \in (H_{N_{ij}}^{-1}(p_{ij}), H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}})\})^2
\end{aligned}$$

At this point we use the almost sure bound (cf. Corollary 2.1 of Helmers, Janssen, Serfling (1988), p. 78)

$$\limsup_{N \rightarrow \infty} \left(\frac{N}{\log N} \right)^{\frac{1}{2}} \sup_x |H_{F_{ij}}(x) - H_{N_{ij}}(x)| = C_m \quad (3.17)$$

a.s. [P], as $N \rightarrow \infty$, with C_m as in the Corollary, as well as the fact that

$$\begin{aligned}
& P_N^*(h_j(X_{i1}^*, \dots, X_{im}^*) \in (H_{N_{ij}}^{-1}(p_{ij}), H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}|X_{i1}^*)) \\
& = m \frac{m!}{N^{m-1}} \sum_{\nu_2 < \dots < \nu_m} I\{h_j(X_{i\nu_2}^*, \dots, X_{i\nu_m}^*) \in \\
& (H_{N_{ij}}^{-1}(p_{ij}), H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}})\} + O(N^{-1}) \quad (3.18)
\end{aligned}$$

a.s. [P], as $N \rightarrow \infty$. Also we have that

$$\begin{aligned}
& E[N^{-m+1} \sum_{\nu_2 < \dots < \nu_m} (I\{h_j(x, X_{i\nu_2}, \dots, X_{i\nu_m}) \in \\
& (H_{N_{ij}}^{-1}(p_{ij}), H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}})\} - P(h_j(x, X_{i\nu_2}, \dots, X_{i\nu_m}) \in (H_{N_{ij}}^{-1}(p_{ij}), \\
& H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}))]^{2r} = O(N^{-r}) \quad (3.19)
\end{aligned}$$

for any integer $r \geq 2$ (cf. Serfling (1980), p. 185), and the easily verified fact that

$$P(h_j(x, X_{i\nu_2}, \dots, X_{i\nu_m}) \in (H_{F_{ij}}^{-1}(p_{ij}), H_{N_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}})) \rightarrow 0, \quad \text{as } N \rightarrow \infty. \quad (3.20)$$

We can conclude that

$$N \text{var}_N^* \{E_N^*(T_{N_{ij}}^*(y_{ij}) - T_{N_{ij}}^*((H_{F_{ij}}^{-1}(p_{ij}) - H_{N_{ij}}(p_{ij}))\sqrt{N})|X_{i_s}^*)\} \rightarrow 0 \quad (3.21)$$

a.s. [P], as $N \rightarrow \infty$. In other words: the quantity (3.15) is indeed small enough for our purposes.

To complete our proof of (3.2) we must still show that

$$\begin{aligned}
& \frac{m^2}{N} \sum_{\nu_1} N^{-m+1} \sum_{\nu_r} \dots \sum_{\nu_m} I\{h_j(X_{i\nu_1}, \dots, X_{i\nu_m}) \leq \\
& H_{F_{ij}}^{-1}(p_{ij})\}^2 \rightarrow m^2 E(P(h_j(X_{i1}, \dots, X_{im}) \leq H_{F_{ij}}^{-1}(p_{ij})|X_{i1}))^2 \quad (3.22)
\end{aligned}$$

a.s. [P], as $N \rightarrow \infty$. But this follows directly from the fact that

$$N^{-m+1} \sum_{\nu_2} \dots \sum_{\nu_m} I\{h_j(X_{i\nu_1}, \dots, X_{i\nu_m}) \leq H_{F_{ij}}^{-1}(p_{ij})\}$$

$$= \frac{(m-1)!}{N^{m-1}} \sum_{\nu_2} \dots \sum_{\nu_m} I\{h_j(X_{i\nu_2}, \dots, X_{i\nu_m}) \leq H_{P_{ij}}^{-1}(p_{ij})\} \quad (3.23)$$

A similar argument gives the desired convergences for the other elements of the covariance matrix in (3.12). This completes the proof of (3.2).

Next we establish the a.s. rate of convergence asserted in (3.3). Our argument follows the pattern of proof given in Theorem 3.1 of Helmers, Janssen, Veraverbeke (1992). Quite similarly, we write

$$\sup_y |P_N^*(N^{\frac{1}{2}}(\hat{\xi}^* - \hat{\xi}) \leq y) - P(N^{\frac{1}{2}}(\hat{\xi} - \xi) \leq y)| \leq \sum_{i=1}^3 I_{iN} \quad (3.24)$$

where, for some suitable constant $K > 0$,

$$I_{1N} = \sup_{\|y\| \leq K(\log N)^{\frac{1}{2}}} |P_N^*(N^{\frac{1}{2}}(\hat{\xi}^* - \hat{\xi}) \leq y) - \Phi(y; 0, m^2 D_{H_F}^{-\frac{1}{2}} \sum D_{H_F}^{-\frac{1}{2}})| \quad (3.25)$$

$$I_{2N} = \sup_{\|y\| > K(\log N)^{\frac{1}{2}}} |P_N^*(N^{\frac{1}{2}}(\hat{\xi}^* - \hat{\xi}) \leq y) - \Phi(y; 0, m^2 D_{H_F}^{-\frac{1}{2}} \sum D_{H_F}^{-\frac{1}{2}})| \quad (3.26)$$

and

$$I_{3N} = \sup_y |P(N^{\frac{1}{2}}(\hat{\xi} - \xi) \leq y) - \Phi(y; 0, m^2 D_{H_F}^{-\frac{1}{2}} \sum D_{H_F}^{-\frac{1}{2}})| \quad (3.27)$$

where $\|\cdot\|$ denote the euclidian norm in \mathbb{R}^{kq} . Because of Theorem 2.1, relation (2.4), we know that $I_{3N} = O(N^{-\frac{1}{2}})$. To treat I_{2N} we apply exactly the same argument as was employed in Helmers, Janssen, Veraverbeke (1992) at a similar point, to establish that $I_{2N} = O(N^{-\frac{1}{2}})$, a.s. [P], as $N \rightarrow \infty$. To show finally that

$$I_{1N} = O(N^{-\frac{1}{2}}(\log N)^{\frac{3}{4}})$$

a.s. [P], as $N \rightarrow \infty$ we combine the fact that

$$\sup_{|y_{ij}| \leq K(\log N)^{\frac{1}{2}}} |\sqrt{N}(p_{ij} - H_{F_{ij}}(H_{F_{ij}}^{-1}(p_{ij}) + y_{ij}N^{-\frac{1}{2}}) - y_{ij}h_{F_{ij}}(\xi_{ij}(p_{ij})))| = O(N^{-\frac{1}{4}}(\log N)^{\frac{3}{4}})$$

a.s. [P], as $N \rightarrow \infty$, for $i = 1, \dots, k$, $j = 1, \dots, q$, together with Theorem 1.16 of Götze (1987) with (3.21) and (3.22). \square

Theorem 3.1 extends results of Singh (1981) and Helmers, Janssen, Veraverbeke (1992) to a wide class of multivariate generalized quantiles, i.e. to multivariate U -quantiles.

4 EXTENSIONS AND EXAMPLES

It is well-known (see, e.g., Bickel and Freedman (1981)) that 'the bootstrap commutes with smooth functions'. In view of this the following useful result is not very suprising:

COROLLARY 4.1. *Suppose that $g : \mathbb{R}^{kq} \rightarrow \mathbb{R}^k$ is continuously differentiable in a neighborhood of $\xi = (\xi_{ij}(p_{ij}), i = 1, \dots, k, j = 1, \dots, q)$ with $\xi_{ij}(p_{ij})$ as in (1.3). In addition, suppose that the assumptions of Theorem 3.1.a. are satisfied. Then, for almost every sample sequence X_1, X_2, \dots*

$$\sup_x |P_N^*(\sqrt{n}(g(\hat{\xi}^*) - g(\hat{\xi})) \leq y) - P(\sqrt{N}(g(\hat{\xi}) - g(\xi)) \leq y)| \rightarrow 0, \text{ as } N \rightarrow \infty \quad (4.1)$$

PROOF. Following the pattern of the proof given by Bickel & Freedman (1981) (4.1) is easily verified using (3.2), (2.3), a Taylor expansion argument, and the fact that $\hat{\xi} \rightarrow \xi$, a.s. [P], as $N \rightarrow \infty$ (cf. Corollary 3.2 of Helmers, Janssen, Serfling (1988)) as well as

$$\hat{\xi}^* - \hat{\xi} \rightarrow 0 \quad \text{in } P^* \text{-probability} \quad (4.2)$$

a.s. [P], as $N \rightarrow \infty$. To verify (4.2) we need the requirement that ξ is uniquely determined. But this is an easy consequence of the local smoothness assumption on H_F . \square

The a.s. rate at which the sup in (4.1) approaches zero is easily checked to be $O(N^{-\frac{1}{4}}(\ln N)^{\frac{3}{4}})$, under somewhat more stringent smoothness assumptions on g and H_F . Because all of this is fairly straightforward in view of Theorem 3.1.6 and Corollary 4.1 we omit further details.

Next we discuss a few specific examples of multivariate U -quantiles. In the first of these we take $q = 1$, $m = 1$ and $h_1(x) = x$ and obtain the k -vector of ordinary marginal p -th sample quantiles. Similarly, by taking $q = 1$, $m = 2$, $h_1(x_1, x_2) = (x_1 + x_2)/2$ we obtain the k -vector of marginal Hodges-Lehmann location estimators, whereas the choice $q = 1$, $m = 2$, $h_1(x_1, x_2) = |x_1 - x_2|$ gives us the k -vector of an estimators of spread proposed by Bickel and Lehmann (1979). In each of these cases Theorem 3.1 tell us that the bootstrap works.

A second type of examples is obtained by taking $q = 2$. For example, let us take all p_{ij} 's equal to $\frac{1}{2}$, $m = 2$, $h_1(x_1, x_2) = (x_1 + x_2)/2$ and $h_2(x_1, x_2) = |x_1 - x_2|$. In this set up $\hat{\xi}$ becomes a vector which consists of k pairs of (marginal) estimators, the first component is the Hodges-Lehmann location estimator and the second one the Bickel-Lehmann estimator of spread. Again, Theorem 3.1 can be employed to find that the bootstrap approximation is asymptotically valid in this case too.

Our third example gives an application of Corollary 4.1. We take $q = 3$, $m = 1$, $h_j(x) = x$, $j = 1, 2, 3$ and $p_{i1} = \frac{1}{2}$, $p_{i2} = \frac{1}{4}$, $p_{i3} = \frac{3}{4}$, $i = 1, \dots, k$ and let $g: \mathbb{R}^{3k} \rightarrow \mathbb{R}^k$ be the map which sends the i -th marginal $(\xi_{i1}, \xi_{i2}, \xi_{i3})$ of ξ into $\xi_{i1}/(\xi_{i3} - \xi_{i2})$, $i = 1, \dots, k$. The resulting estimator is the k -vector of marginal sample medians divided by the marginal sample interquartile ranges. Corollary 4.1 asserts that the bootstrap also works here. Of course one can easily supplement this example with many others: e.g. one may consider a linear combination of a fixed number of marginal ordinary sample quantiles in each component or - to give another example - consider the the quotient of the Bickel-Lehmann estimator of spread and the Hodges-Lehmann location estimator in each component (i.e. a generalized 'coefficient of variation').

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