

# Supplement to ”Applications of Distance Correlation to Time Series”

RICHARD A. DAVIS<sup>1,\*</sup> MUNEYA MATSUI<sup>2,\*\*</sup> THOMAS MIKOSCH<sup>3,†</sup> and PHYLLIS WAN<sup>1,‡</sup>

<sup>1</sup>*Department of Statistics, Columbia University, 1255 Amsterdam Ave, New York, NY 10027, USA. E-mail: [\\*rdavis@stat.columbia.edu](mailto:*rdavis@stat.columbia.edu); [‡phyllis@stat.columbia.edu](mailto:‡phyllis@stat.columbia.edu)*

<sup>2</sup>*Department of Business Administration, Nanzan University, 18 Yamazato-cho, Showa-ku, Nagoya 466-8673, Japan. E-mail: [\\*\\*mmuneya@gmail.com](mailto:**mmuneya@gmail.com)*

<sup>3</sup>*Department of Mathematics, University of Copenhagen, Universitetsparken 5, DK-2100 Copenhagen, Denmark E-mail: [†mikosch@math.ku.dk](mailto:†mikosch@math.ku.dk)*

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This supplement provides the omitted technical details to the proofs of Theorem 4.2 and Lemma 4.1, in [Davis et al. \(2016\)](#). The setting, notation, equation reference numbers are retained from the main paper. For convenience, the corresponding results in [Davis et al. \(2016\)](#) using the same reference numbers are stated before the proofs. The Remarks 3.4 and 3.9 from the main paper have also been duplicated here.

## Proof of Theorem 4.2

For the convenience of the reader, we recall two remarks from [Davis et al. \(2016\)](#) which are mentioned in the proof.

**Remark 3.4.** *If  $(X_j)$  and  $(Y_j)$  are two independent iid sequences then the statement of Theorem 3.2 (1) remains valid if for some  $\alpha \in (0, 2]$ ,  $\mathbb{E}[|X|^\alpha] + \mathbb{E}[|Y|^\alpha] < \infty$  and*

$$\int_{\mathbb{R}^{p+q}} (1 \wedge |s|^\alpha)(1 \wedge |t|^\alpha) \mu(ds, dt) < \infty. \quad (3.8)$$

**Remark 3.9.** *From the proof of Theorem 3.2 (the central limit theorem for the multivariate empirical characteristic function) it follows that  $G_h$  has covariance function*

$$\begin{aligned} \Gamma((s, t), (s', t')) &= \text{cov}(G_h(s, t), G_h(s', t')) \\ &= \sum_{j \in \mathbb{Z}} \mathbb{E}[(e^{i \langle s, X_0 \rangle} - \varphi_X(s))(e^{i \langle t, Y_h \rangle} - \varphi_Y(t)) \\ &\quad \times (e^{-i \langle s', X_j \rangle} - \varphi_X(-s'))(e^{-i \langle t', Y_{j+h} \rangle} - \varphi_Y(-t'))]. \end{aligned} \quad (3.9)$$

In the special case when  $(X_t)$  and  $(Y_t)$  are independent sequences  $G_h$  is the same across all  $h$  with covariance function

$$\Gamma((s, t), (s', t')) = (\varphi_X(s - s') - \varphi_X(s)\varphi_X(s'))(\varphi_Y(t - t') - \varphi_Y(t)\varphi_Y(t')).$$

Since  $G_h$  is centered Gaussian its squared  $L^2$ -norm  $\|G_h\|_\mu^2$  has a weighted  $\chi^2$ -distribution; see [Kuo \(1975\)](#), Chapter 1. The distribution of  $\|G_h\|_\mu^2$  is not tractable and therefore one needs resampling methods for determining its quantiles.

**Theorem 4.2.** Consider a causal AR( $p$ ) process with iid noise  $(Z_t)$ . Assume

$$\int_{\mathbb{R}^2} [(1 \wedge |s|^2)(1 \wedge |t|^2)\mu(ds, dt) + (s^2 + t^2)\mathbf{1}(|s| \wedge |t| > 1)\mu(ds, dt)] < \infty. \quad (4.7)$$

1. If  $\sigma^2 = \text{Var}(Z) < \infty$ , then

$$nT_{n,\mu}^{\widehat{Z}}(h) \xrightarrow{d} \|G_h + \xi_h\|_\mu^2, \quad \text{and} \quad nR_{n,\mu}^{\widehat{Z}}(h) \xrightarrow{d} \frac{\|G_h + \xi_h\|_\mu^2}{T_\mu^Z(0)}, \quad (4.8)$$

where  $(G_h, \xi_h)$  are jointly Gaussian limit random fields on  $\mathbb{R}^2$ . The covariance structure of  $G_h$  is specified in Remark 3.9 above for the sequence  $((Z_t, Z_{t+h}))$ ,  $\xi_h$  and the joint limit structure of  $(G_h, \xi_h)$  are given in Lemma 4.1 below.

2. If  $Z$  is in the domain of attraction of a stable law of index  $\alpha \in (0, 2)$ , i.e.,  $\mathbb{P}(|Z| > x) = x^{-\alpha}L(x)$  for  $x > 0$  and  $L(\cdot)$  is a slowly varying function at  $\infty$ , and

$$\frac{\mathbb{P}(Z > x)}{\mathbb{P}(|Z| > x)} \rightarrow p \quad \text{and} \quad \frac{\mathbb{P}(Z < -x)}{\mathbb{P}(|Z| > x)} \rightarrow 1 - p$$

as  $x \rightarrow \infty$  for some  $p \in [0, 1]$  ([Feller \(1971\)](#), p. 313). Then we have

$$nT_{n,\mu}^{\widehat{Z}}(h) \xrightarrow{d} \|G_h\|_\mu^2 \quad \text{and} \quad nR_{n,\mu}^{\widehat{Z}}(h) \xrightarrow{d} \frac{\|G_h\|_\mu^2}{T_\mu^Z(0)}, \quad (4.9)$$

where  $G_h$  is a Gaussian limit random field on  $\mathbb{R}^2$ . The covariance structure of  $G_h$  is specified in Remark 3.9 for the sequence  $((Z_t, Z_{t+h}))$ .

We prove the result for the residuals calculated from least square estimates (LSEs). One may show that the same result holds for maximum likelihood and Yule-Walker estimates. We recall the relevant asymptotic results for the least squares estimator from Section 4 in [Davis et al. \(2016\)](#); we use the same reference numbers for mathematical formulæ as in [Davis et al. \(2016\)](#). The least-squares estimator  $\widehat{\phi}$  of  $\phi$  satisfies the relation

$$\widehat{\phi} - \phi = \Gamma_{n,p}^{-1} \frac{1}{n} \sum_{t=p+1}^n \mathbf{X}_{t-1} Z_t,$$

where

$$\Gamma_{n,p} = \frac{1}{n} \sum_{t=p+1}^n \mathbf{X}_{t-1}^T \mathbf{X}_{t-1}.$$

If  $\sigma^2 = \text{var}(Z_t) < \infty$ , we have by the ergodic theorem,

$$\Gamma_{n,p} \xrightarrow{\text{a.s.}} \Gamma_p = (\gamma_X(j-k))_{1 \leq j,k \leq p}, \quad \text{where } \gamma_X(h) = \text{cov}(X_0, X_h), h \in \mathbb{Z}. \quad (4.1)$$

Causality of the process implies that the partial sum  $\sum_{t=p+1}^n \mathbf{X}_{t-1} Z_t$  is a martingale and applying the martingale central limit theorem yields

$$\sqrt{n} (\hat{\phi} - \phi) \xrightarrow{d} \mathbf{Q}, \quad (4.2)$$

where  $\mathbf{Q}$  is  $N(\mathbf{0}, \sigma^2 \Gamma_p^{-1})$  distributed.

Keeping this in mind, we start with a joint central limit theorem for  $C_n^Z$  and  $\hat{\phi}$ .

**Lemma 4.1.** *Consider an iid sequence  $(Z_t)$  with finite variance.*

1. For every  $h \geq 0$ ,

$$\sqrt{n} (C_n^Z, \hat{\phi} - \phi) \xrightarrow{d} (G_h, \mathbf{Q}),$$

where the convergence is in  $\mathcal{C}(K) \times \mathbb{R}^p$ ,  $K \subset \mathbb{R}^2$  is a compact set,  $G_h$  is the limit process of  $C_n^Z$  with covariance structure specified in Remark 3.9 for the sequence  $((Z_t, Z_{t+h}))$ ,  $\mathbf{Q}$  is the limit in (4.2),  $(G_h, \mathbf{Q})$  are mean-zero and jointly Gaussian with covariance matrix

$$\text{cov}(G_h(s, t), \mathbf{Q}) = -\varphi'_Z(s) \varphi'_Z(t) \Gamma_p^{-1} \Psi_h, \quad s, t \in \mathbb{R}, \quad (4.4)$$

where  $\Psi_h = (\psi_{h-j})_{j=1, \dots, p}$  and  $\varphi'_Z$  is the first derivative of  $\varphi_Z$ .

2. For every  $h \geq 0$ ,

$$\sqrt{n} (C_n^Z, C_n^{\hat{Z}} - C_n^Z) \xrightarrow{d} (G_h, \xi_h),$$

where  $(G_h, \mathbf{Q})$  are specified in (4.4) and

$$\xi_h(s, t) = t \varphi_Z(t) \varphi'_Z(s) \Psi_h^T \mathbf{Q}, \quad (s, t) \in K, \quad (4.5)$$

the convergence is in  $\mathcal{C}(K, \mathbb{R}^2)$ ,  $K \subset \mathbb{R}^2$  is a compact set. In particular, we have

$$\sqrt{n} C_n^{\hat{Z}} \xrightarrow{d} G_h + \xi_h. \quad (4.6)$$

**Proof of part (1).** We observe that, uniformly for  $(s, t) \in K$ ,

$$\begin{aligned} C_n^Z(s, t) &= \frac{1}{n} \sum_{j=1}^{n-h} e^{isZ_j + itZ_{j+h}} - \frac{1}{n} \sum_{j=1}^{n-h} e^{isZ_j} \frac{1}{n} \sum_{j=1}^{n-h} e^{itZ_{j+h}} \\ &= \frac{1}{n} \sum_{j=1}^n (e^{isZ_j} - \varphi_Z(s)) (e^{itZ_{j+h}} - \varphi_Z(t)) \\ &\quad - \frac{1}{n} \sum_{j=1}^n (e^{isZ_j} - \varphi_Z(s)) \frac{1}{n} \sum_{j=1}^n (e^{itZ_j} - \varphi_Z(t)) + O_{\mathbb{P}}(n^{-1}). \end{aligned}$$

In view of the functional central limit theorem for the empirical characteristic function of an iid sequence (see Csörgő (1981a, 1981b)) we have uniformly for  $(s, t) \in K$ ,

$$\begin{aligned} \sqrt{n} C_n^Z(s, t) &= \frac{1}{\sqrt{n}} \sum_{j=1}^n (e^{isZ_j} - \varphi_Z(s)) (e^{itZ_{j+h}} - \varphi_Z(t)) + O_{\mathbb{P}}(n^{-1/2}) \\ &= I_n(s, t) + O_{\mathbb{P}}(n^{-1/2}). \end{aligned}$$

Therefore it suffices to study the convergence of the finite-dimensional distributions of  $(I_n, \sqrt{n}(\hat{\phi} - \phi))$ . In view of (4.1) it suffices to show the convergence of the finite-dimensional distributions of  $(I_n, (1/\sqrt{n}) \sum_{j=1}^n \mathbf{X}_{j-1} Z_j)$ . This convergence follows by an application of the martingale central limit theorem and the Cramér-Wold device. It remains to determine the limiting covariance structure, taking into account the causality of the process  $(X_t)$ . We have

$$\text{cov}\left(I_n, \frac{1}{\sqrt{n}} \sum_{j=1}^n \mathbf{X}_{j-1} Z_j\right) = \frac{1}{n} \mathbb{E} \left[ \sum_{j=1}^n \sum_{k=1}^n (e^{isZ_j} - \varphi_Z(s)) (e^{itZ_{j+h}} - \varphi_Z(t)) \mathbf{X}_{k-1} Z_k \right].$$

By causality,  $X_k$  and  $Z_j$  are independent for  $k < j$ . Hence  $\mathbb{E}[(e^{isZ_j} - \varphi_Z(s))(e^{itZ_{j+h}} - \varphi_Z(t)) X_{l-k} Z_l]$  is non-zero if and only if  $l = j + h$  and  $k \leq h$ , resulting in

$$\begin{aligned} &\mathbb{E}[(e^{isZ_j} - \varphi_Z(s))(e^{itZ_{j+h}} - \varphi_Z(t)) X_{l-k} Z_l] \\ &= \mathbb{E}[X_{j+h-k} (e^{isZ_j} - \varphi_Z(s))] \mathbb{E}[Z_{j+h} (e^{itZ_{j+h}} - \varphi_Z(t))] \\ &= \psi_{h-k} \mathbb{E}[Z (e^{isZ} - \varphi_Z(s))] \mathbb{E}[Z (e^{itZ} - \varphi_Z(t))] \\ &= -\psi_{h-k} i \mathbb{E}[Z e^{isZ}] i \mathbb{E}[Z e^{itZ}] \\ &= -\psi_{h-k} \varphi'_Z(s) \varphi'_Z(t). \end{aligned}$$

This implies (4.4). □

**Proof of part (2).** We observe that, uniformly for  $(s, t) \in K$ ,

$$\begin{aligned}
& C_n^{\hat{Z}}(s, t) - C_n^Z(s, t) \\
&= \frac{1}{n} \sum_{j=1}^n e^{isZ_j + itZ_{j+h}} \left( e^{i(\phi - \hat{\phi})^T (s\mathbf{X}_{j-1} + t\mathbf{X}_{j+h-1})} - 1 \right) \\
&+ \frac{1}{n} \sum_{j=1}^n \left( 1 - e^{i(\phi - \hat{\phi})^T s\mathbf{X}_{j-1}} \right) e^{isZ_j} \frac{1}{n} \sum_{j=1}^n e^{itZ_{j+h}} \\
&+ \frac{1}{n} \sum_{j=1}^n e^{i(\phi - \hat{\phi})^T s\mathbf{X}_{j-1} + isZ_j} \frac{1}{n} \sum_{j=1}^n \left( 1 - e^{i(\phi - \hat{\phi})^T t\mathbf{X}_{j+h-1}} \right) e^{itZ_{j+h}} + O_{\mathbb{P}}(n^{-1}) \\
&= E_{n1}(s, t) + E_{n2}(s, t) + E_{n3}(s, t) + O_{\mathbb{P}}(n^{-1}).
\end{aligned} \tag{S.1}$$

Write

$$\tilde{E}_{n1}(s, t) = i(\phi - \hat{\phi})^T \frac{1}{n} \sum_{j=1}^n (s\mathbf{X}_{j-1} + t\mathbf{X}_{j+h-1}) e^{isZ_j + itZ_{j+h}}.$$

In view of the uniform ergodic theorem, (4.2) and the causality of  $(X_t)$  we have

$$\begin{aligned}
\sqrt{n}\tilde{E}_{n1}(s, t) &\xrightarrow{d} -i\mathbf{Q}^T \mathbb{E}[(s\mathbf{X}_0 + t\mathbf{X}_h) e^{i(sZ_1 + tZ_{h+1})}] \\
&= -t\varphi_Z(t)\varphi'_Z(s)\Psi_h^T \mathbf{Q} = \xi_h(s, t),
\end{aligned} \tag{S.3}$$

where the convergence is in  $\mathcal{C}(K)$ . By virtue of part (1) and the mapping theorem we have the joint convergence  $\sqrt{n}(C_n^Z, \tilde{E}_{n1}) \xrightarrow{d} (G_h, \xi_h)$  in  $\mathcal{C}(K, \mathbb{R}^2)$ . Denoting the sup-norm in  $\mathcal{C}(K)$  by  $\|\cdot\|$ , it remains to show that  $\sqrt{n}(\|E_{n2}\| + \|E_{n3}\| + \|E_{n1} - \tilde{E}_{n1}\|) \xrightarrow{\mathbb{P}} 0$ . The proof for  $E_{n2}$  and  $E_{n3}$  is analogous to (S.3) by observing that the limiting expectation is zero. We have by a Taylor expansion for some positive constant  $c$ ,

$$\sqrt{n}\|E_{n1}(s, t) - \tilde{E}_{n1}(s, t)\| \leq c|\sqrt{n}(\phi - \hat{\phi})|^2 \sup_{(s,t) \in K} \frac{1}{n^{3/2}} \sum_{j=1}^n |s\mathbf{X}_{j-1} + t\mathbf{X}_{j+h-1}|^2 \xrightarrow{\mathbb{P}} 0.$$

In the last step we used the uniform ergodic theorem and (4.2).  $\square$

**Proof of Theorem 4.2(1).** We proceed as in the proof of Theorem 3.2. By virtue of (4.6) and the continuous mapping theorem we have

$$\int_{K_\delta} |\sqrt{n}C_n^{\hat{Z}}(s, t)|^2 \mu(ds, dt) \xrightarrow{d} \int_{K_\delta} |G(s, t) + \xi_h(s, t)|^2 \mu(ds, dt), \quad n \rightarrow \infty.$$

Thus it remains to show that

$$\lim_{\delta \downarrow 0} \limsup_{n \rightarrow \infty} \mathbb{P} \left( \int_{K_\delta} |\sqrt{n}C_n^{\hat{Z}}(s, t)|^2 \mu(ds, dt) > \varepsilon \right) = 0, \quad \varepsilon > 0. \tag{S.4}$$

Following the lines of the proof of Theorem 3.2, we have

$$\lim_{\delta \downarrow 0} \limsup_{n \rightarrow \infty} \int_{K_\delta^c} \mathbb{E}[|\sqrt{n}C_n^Z(s, t)|^2] \mu(ds, dt) = 0;$$

see also Remark 3.4. Thus it suffices to show

$$\lim_{\delta \downarrow 0} \limsup_{n \rightarrow \infty} \mathbb{P} \left( \int_{K_\delta^c} |\sqrt{n}(C_n^{\hat{Z}}(s, t) - C_n^Z(s, t))|^2 \mu(ds, dt) > \varepsilon \right) = 0, \quad \varepsilon > 0.$$

For convenience we redefine

$$C_n^Z = \frac{1}{n} \sum_{j=p+1}^{n-h} e^{isZ_j + itZ_{j+h}} - \frac{1}{n} \sum_{j=p+1}^{n-h} e^{isZ_j} \frac{1}{n} \sum_{j=p+1}^{n-h} e^{itZ_{j+h}}.$$

This version does not change previous results for  $C_n^Z$ .

Using telescoping sums, we have for  $\bar{n} = n - p - h$ ,

$$\begin{aligned} & \frac{\bar{n}}{n} (C_n^{\hat{Z}}(s, t) - C_n^Z(s, t)) \\ &= \frac{1}{\bar{n}} \sum_{j=p+1}^{n-h} A_j B_j - \frac{1}{\bar{n}} \sum_{j=p+1}^{n-h} A_j \frac{1}{\bar{n}} \sum_{j=p+1}^{n-h} B_j - \frac{1}{\bar{n}} \sum_{j=p+1}^{n-h} U_j \sum_{j=p+1}^{n-h} B_j - \frac{1}{\bar{n}} \sum_{j=p+1}^{n-h} V_j \sum_{j=p+1}^{n-h} A_j \\ & \quad + \frac{1}{\bar{n}} \sum_{j=p+1}^{n-h} U_j B_j + \frac{1}{\bar{n}} \sum_{j=p+1}^{n-h} V_j A_j =: \sum_{j=1}^6 I_{nj}(s, t), \end{aligned}$$

where, suppressing the dependence on  $s, t$  in the notation,

$$\begin{aligned} U_j &= e^{isZ_j} - \varphi_Z(s), & V_j &= e^{itZ_{j+h}} - \varphi_Z(t), \\ A_j &= e^{isZ_j} (e^{is(\phi - \hat{\phi})' X_{j-1}} - 1), & B_j &= e^{itZ_{j+h}} (e^{is(\phi - \hat{\phi})' X_{j+h-1}} - 1). \end{aligned}$$

Write  $K_n = |\sqrt{n}(\phi - \hat{\phi})|$  and  $c > 0$  for any positive constant which may differ from line to line. By Taylor expansions we have

$$\begin{aligned} n |I_{n1}(s, t)|^2 &\leq \left( \frac{\sqrt{n}}{\bar{n}} \sum_{j=p+1}^{n-h} |A_j B_j| \right)^2 \\ &\leq c \left( \frac{\sqrt{n}}{\bar{n}} \sum_{j=p+1}^{n-h} (1 \wedge |s| |\phi - \hat{\phi}| |X_{j-1}|) (1 \wedge |t| |\phi - \hat{\phi}| |X_{j+h-1}|) \right)^2 \\ &\leq c \left( \min(|s| K_n^2 \frac{1}{\bar{n}^{3/2}} \sum_{j=p+1}^{n-h} |X_{j-1}| |X_{j+h-1}|, |s| K_n \frac{1}{\bar{n}} \sum_{j=p+1}^{n-h} |X_{j-1}|, \right. \\ & \quad \left. |t| K_n \frac{1}{\bar{n}} \sum_{j=p+1}^{n-h} |X_{j+h-1}| \right)^2. \end{aligned}$$

The quantities  $K_n$  are stochastically bounded. From ergodic theory,  $n^{-1} \sum_{j=1}^n |X_j| = O_{\mathbb{P}}(1)$  and  $n^{-3/2} \sum_{j=1}^n |X_j X_{j+h}| = o_{\mathbb{P}}(1)$ . Hence

$$n |I_{n1}(s, t)|^2 \leq \min(s^2, t^2, (st)^2) O_{\mathbb{P}}(1) \leq ((1 \wedge s^2)(1 \wedge t^2) + (s^2 + t^2)\mathbf{1}(|s| \wedge |t| \geq 1)) O_{\mathbb{P}}(1),$$

where the term  $O_{\mathbb{P}}(1)$  does not depend on  $s$  and  $t$ . Thus we conclude for  $k = 1$  that

$$\lim_{\delta \downarrow 0} \limsup_{n \rightarrow \infty} \mathbb{P} \left( n \int_{K_n^\delta} |I_{nk}(s, t)|^2 \mu(ds, dt) > \varepsilon \right) = 0, \quad \varepsilon > 0. \quad (\text{S.5})$$

A similar argument yields

$$\begin{aligned} & n |I_{n2}(s, t)|^2 \\ & \leq \left( \frac{\sqrt{n}}{\bar{n}^2} \sum_{j,k=p+1}^{n-h} |A_j| |B_k| \right)^2 \\ & \leq \left( \frac{\sqrt{n}}{\bar{n}^2} \sum_{j,k=p+1}^{n-h} (1 \wedge |s| |\phi - \hat{\phi}| |X_{j-1}|) (1 \wedge |t| |\phi - \hat{\phi}| |X_{k+h-1}|) \right)^2 \\ & \leq c \left( \min \left( |st| K_n^2 \frac{1}{\bar{n}^{5/2}} \sum_{j,k=p+1}^{n-h} |X_{j-1} X_{k+h-1}|, \right. \right. \\ & \quad \left. \left. |s| K_n \frac{1}{\bar{n}} \sum_{j=p+1}^{n-h} |X_{j-1}|, |t| K_n \frac{1}{\bar{n}} \sum_{k=p+1}^{n-h} |X_{k+h-1}| \right) \right)^2 \\ & \leq \min(s^2, t^2, (st)^2) O_{\mathbb{P}}(1). \end{aligned}$$

Then (S.5) holds for  $k = 2$ . Taylor expansions also yield

$$\begin{aligned} n |I_{n3}(s, t)|^2 & \leq \left( \frac{\sqrt{n}}{\bar{n}^2} \sum_{j,k=p+1}^{n-h} |U_j| |B_k| \right)^2 \\ & \leq c \left( \frac{\sqrt{n}}{\bar{n}^2} \sum_{j,k=p+1}^{n-h} (1 \wedge \frac{1}{2} |s| (|Z_j| + \mathbb{E}|Z|)) (1 \wedge |t| |\phi - \hat{\phi}| |X_{k+h-1}|) \right)^2 \\ & \leq \min(t^2, (st)^2) O_{\mathbb{P}}(1). \end{aligned}$$

This proves (S.5) for  $k = 3$ . By a symmetry argument but with the corresponding bound

$\min(s^2, (st)^2) O_{\mathbb{P}}(1)$ , (S.5) for  $k = 4$  follows as well. By Taylor expansion, we also have

$$\begin{aligned} n |I_{n5}(s, t)|^2 &\leq \left( \frac{\sqrt{n}}{\bar{n}} \sum_{j=p+1}^{n-h} |U_j| |B_j| \right)^2 \\ &\leq c \left( \frac{\sqrt{n}}{\bar{n}} \sum_{j=p+1}^{n-h} (1 \wedge \frac{1}{2} |s| (|Z_j| + \mathbb{E}|Z|)) (1 \wedge |t| |\phi - \hat{\phi}| |X_{j+h-1}|) \right)^2 \\ &\leq \min(t^2, (st)^2) O_{\mathbb{P}}(1). \end{aligned}$$

We may conclude that (S.5) holds for  $k = 5$ . The case  $k = 6$  follows in a similar way with the corresponding bound  $\min(s^2, (st)^2) O_{\mathbb{P}}(1)$ .  $\square$

**Proof of Theorem 4.2(2).** We follow the proof of Theorem 4.2(1) by first showing that

$$\sqrt{n} C_n^{\hat{Z}} \xrightarrow{d} G_h \quad (\text{S.6})$$

in  $\mathcal{C}(K)$  for  $K \subset \mathbb{R}^2$  compact, and then (S.4). The convergence  $\sqrt{n} C_n^Z \xrightarrow{d} G_h$  in  $\mathcal{C}(K)$  continues to hold as in the proof of Theorem 4.2(1) since the conditions in Csörgő (1981a,1981b) are satisfied if some moment of  $Z$  is finite. For (S.6) it suffices to show that

$$\sqrt{n} (C_n^{\hat{Z}} - C_n^Z) \xrightarrow{p} 0 \quad (\text{S.7})$$

in  $\mathcal{C}(K)$ . Recalling the decomposition (S.2), we now can show directly that

$\sup_{|s|, |t| \leq M} \sqrt{n} |E_{ni}(s, t)| \xrightarrow{p} 0$  for any  $M > 0$  and  $i = 1, 2, 3$ , which implies (S.7). We focus only on the case  $i = 1$  to illustrate the method; the cases  $i = 2, 3$  are analogous. We observe that for  $\delta > 0$ ,

$$\begin{aligned} \sup_{|s|, |t| \leq M} \sqrt{n} |E_{n1}(s, t)| &\leq \sup_{|s|, |t| \leq M} \sqrt{n} |\phi - \hat{\phi}| \frac{1}{n} \sum_{j=p+1}^{n-h} |s \mathbf{X}_{j-1} + t \mathbf{X}_{j+h-1}| \\ &\leq M n^{\frac{1}{\delta}} |\phi - \hat{\phi}| n^{-\frac{1}{\delta} - \frac{1}{2}} \sum_{j=1}^n |\mathbf{X}_j|. \end{aligned} \quad (\text{S.8})$$

On the other hand, under the conditions of Theorem 4.2(2) Hamann and Kanter (1977) showed for  $\delta > \alpha$ ,

$$n^{1/\delta} (\phi - \hat{\phi}) \xrightarrow{\text{a.s.}} 0.$$

For  $\alpha \in (1, 2)$ ,  $\mathbb{E}[|\mathbf{X}|] < \infty$  and since we can choose  $\delta = 2$  such that  $1/\delta + 1/2 = 1$ . The ergodic theorem finally yields that the right-hand side in (S.8) converges to zero a.s. As regards the case  $\alpha \in (0, 1]$ , we have  $\mathbb{E}[|\mathbf{X}|^{\alpha-\gamma}] < \infty$  for any small  $\gamma$  and

$$\mathbb{E} \left[ \left| n^{-1/\delta - 1/2} \sum_{j=1}^n |\mathbf{X}_j| \right|^{\alpha-\gamma} \right] \leq n^{-(\alpha-\gamma)(1/\delta + 1/2) + 1} \mathbb{E}[|\mathbf{X}|^{\alpha-\gamma}] \rightarrow 0.$$

If we choose  $\delta$  close to  $\alpha$  and  $\gamma$  close to zero the right-hand side in (S.8) converges to zero in probability.

Using the same bounds as in part (1), but writing this time  $K_n = n^{1/\delta}|\phi - \hat{\phi}|$ , we have

$$\begin{aligned} n |I_{n1}(s, t)|^2 &\leq c \left( \min \left( |s t| K_n^2 n^{-1/2-2/\delta} \sum_{j=1}^n |X_{j-1} X_{j+h-1}|, |s| K_n n^{-1/\delta-1/2} \sum_{j=0}^n |X_j|, \right. \right. \\ &\quad \left. \left. |t| K_n n^{-1/\delta-1/2} \sum_{j=0}^n |X_j| \right) \right)^2 \\ &\leq c \min(|s t|^2, |s|^2, |t|^2) \max \left( K_n^2 n^{-1/2-2/\delta} \sum_{j=1}^n |X_{j-1} X_{j+h-1}|, \right. \\ &\quad \left. K_n n^{-1/\delta-1/2} \sum_{j=0}^n |X_j| \right)^2. \end{aligned}$$

The same argument as above shows that  $n^{-1/\delta-1/2} \sum_{j=0}^n |X_j| = O_{\mathbb{P}}(1)$  for  $\delta$  close to  $\alpha$ . Since  $2|X_{j-1} X_{j+h-1}| \leq X_{j-1}^2 + X_{j+h-1}^2$  a similar argument shows that  $n^{-1/2-2/\delta} \sum_{j=1}^n |X_{j-1} X_{j+h-1}| = O_{\mathbb{P}}(1)$ . These facts establish (S.5) for  $k = 1$ . The same arguments show that bounds analogous to part (1) can be derived for  $n |I_{nk}(s, t)|^2$  for  $k = 2, \dots, 6$ . We omit further details.  $\square$

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