

ASYMPTOTIC DISTRIBUTION OF A CRAMÉR-VON MISES TYPE STATISTIC FOR TESTING SYMMETRY WHEN THE CENTER IS ESTIMATED

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Summary

In this paper we investigate the effect of estimating the center of symmetry on a Cramér-von Mises type statistic for testing the symmetry of a distribution function. The test statistic is defined by

$$nT_0[F_n] = n \int_{-\infty}^{\infty} \{F_n(x) + F_n(2S[F_n] - x) - 1\}^2 dF_n(x),$$

where F_n is the empirical distribution function and $S[F_n]$ is an estimator of the center of F which is consistent with the order $n^{1/2}$ and has von Mises derivative. The asymptotic distribution of $nT_0[F_n]$ under the null hypothesis is obtained. The distribution depends on the distribution F and on the estimator $S[F_n]$.

1. Introduction

Let $X_1, X_2, \dots, X_n, \dots$ be a sequence of i.i.d. random variables defined on a single probability space $(\mathcal{Q}, \mathcal{B}, P)$ with a continuous distribution function F . F_n denotes the empirical distribution function of the variables X_1, X_2, \dots, X_n . There are many statistics for testing the null hypothesis (H_0) that F is symmetric about a specified value. For example we may mention a (weighted) sign test statistic and a Cramér-von Mises type statistic for testing symmetry. The latter is investigated by Filippova [1] (Example 9) and Rothman and Woodroffe [5].

Now we consider a problem of testing the null hypothesis (H) that F is symmetric about an unknown center. Since it is very rare in practice that one knows the center of symmetry, we can say that the hypothesis H is more practical than the hypothesis H_0 . Under the hypothesis H we must estimate the center of F using some estimator. The problem of finding the best estimator is very difficult because we

do not know the distribution shape of F . But at any rate we can use any estimator satisfying the assumption (A2) in Section 2, for example Huber's M -estimator and L -estimator. Then the statistic $nT_0[F_n]$ defined in (1.1) below can be regarded as a test statistic of the hypothesis H ,

$$(1.1) \quad nT_0[F_n] = n \int_{-\infty}^{\infty} \{F_n(x) + F_n(2S[F_n] - x) - 1\}^2 dF_n(x),$$

where $S[F_n]$ is an estimator of the center of F . The statistic is a Cramér-von Mises type statistic for testing symmetry with the center estimated. It is very important, I think, for practical purposes investigating its distribution.

In Section 2 we give the asymptotic distribution of $nT_0[F_n]$ under the null hypothesis H . Let $nT[F_n]$ be defined by

$$(1.2) \quad nT[F_n] = n \int_{-\infty}^{\infty} \{F_n(x) + F_n(2S[F_n] - x) - 1\}^2 dF(x),$$

which is replaced the measure F_n of the integral of $nT_0[F_n]$ by F . In Theorem 1, $nT_0[F_n]$ and $nT[F_n]$ are shown to be asymptotically equivalent. In Theorem 2 we investigate the asymptotic distribution of $nT[F_n]$. The asymptotic distribution depends on the distribution F and the estimator S . After all we arrive at the conclusion that estimating the unknown center has a very severe effect on the asymptotic distribution of the Cramér-von Mises type statistic for testing symmetry.

2. Results

In this section we study the asymptotic distribution of $nT_0[F_n]$ under the null hypothesis H . Suppose that $X_1, X_2, \dots, X_n, \dots$ is a sequence of i.i.d. random variables with a continuous distribution function F . Let m be the median of F . In order to state assumptions on F and S , we need two definitions. Suppose a real valued functional R is defined on a set σ_R of real functions of a real argument.

DEFINITION 1. The functional R is called m times differentiable at the point $V \in \sigma_R$ with respect to the set $\tau \subset \sigma_R$ which is assumed to be star-shaped at the point V if the following conditions are satisfied:

- (1) For any $t \in [0, 1]$, $p = 1, 2, \dots, m$, and any function $W \in \tau$

$$\frac{d^p}{dt^p} R[(1-t)V + tW]$$

exists.

- (2) There exist functions $R^{(p)}[V: y_1, \dots, y_p]$ of p arguments, $p =$

$1, \dots, m$, which depend on V , such that for any function $W \in \tau$, the relation

$$\begin{aligned} & \left. \frac{d^p}{dt^p} R[(1-t)V + tW] \right|_{t=0} \\ &= \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} R^{(p)}[V: y_1, \dots, y_p] \prod_{i=1}^p d[W(y_i) - V(y_i)] , \\ & \qquad \qquad \qquad p=1, \dots, m , \end{aligned}$$

holds.

DEFINITION 2 (Filippova). The functional R is called a Mises functional of order m at the point F (F is a distribution function) if the following conditions are satisfied:

(1) There exists a star-shaped set $\tau_R \subset \sigma_R$ at the point F such that

$$\lim_{n \rightarrow \infty} P \{F_n \in \tau_R\} = 1 .$$

(2) The functional R is m times differentiable at the point F with respect to the set τ_R .

(3) For any $\varepsilon > 0$, $\delta > 0$ and $p=1, \dots, m$, it holds that

$$\lim_{n \rightarrow \infty} P \left\{ n^{(p/2)-\delta} \sup_{0 \leq t \leq 1} \left| \frac{d^p}{dt^p} R[(1-t)F + tF_n] \right| > \varepsilon \right\} = 0 .$$

ASSUMPTIONS

(A1) F is three times differentiable except for a set of Lebesgue measure zero.

(A2) $S[F_n]$ is a consistent estimator of m with the order $n^{1/2}$ and is a Mises functional of order 3 at F .

THEOREM 1. If Assumptions (A1) and (A2) are satisfied,

$$(2.1) \quad \int_{-\infty}^{\infty} n \{F_n(x) + F_n(2S[F_n] - x) - 1\}^2 d[F_n(x) - F(x)]$$

converges to zero in probability as $n \rightarrow \infty$ under the null hypothesis H .

Before the proof of Theorem 1 we state two lemmas.

LEMMA 1 (Pyke and Shorack [4]). There exists a sequence of random processes $\{\Gamma_n(t): 0 \leq t \leq 1\}$, $n \geq 1$ which have the same distributions as empirical distribution functions of independent random variables with uniform distribution on $[0, 1]$ and there exists a Brownian bridge $\{\beta(t): 0 \leq t \leq 1\}$ such that $\{\Gamma_n(t): 0 \leq t \leq 1\}$, $n \geq 1$ and $\{\beta(t): 0 \leq t \leq 1\}$ are defined on a single probability space and they satisfy the following relation

$$\sup_t |n^{1/2}(\Gamma_n(t) - t) - \beta(t)| \rightarrow 0 \quad \text{almost surely as } n \rightarrow \infty.$$

We define $h_n(x)$ and $h(x)$ by

$$\begin{aligned} h_n(x) &= n \{ \Gamma_n(F(x)) + \Gamma_n(F(2S[\Gamma_n(F)] - x)) - 1 \}^2, \\ h(x) &= \left\{ \beta(F(x)) + \beta(F(2m - x)) \right. \\ &\quad \left. + 2f(2m - x) \int_0^1 S^{(1)}[F: F^{-1}(s)] d\beta(s) \right\}^2, \end{aligned}$$

where f is the derivative of F and $S^{(1)}[F: \cdot]$ is the real valued function of a real argument which exists from the assumption (A2) (see Definition 1 and Definition 2).

LEMMA 2. *If Assumptions (A1) and (A2) are satisfied,*

$$\sup_x |h_n(x) - h(x)| \rightarrow 0 \quad \text{in probability as } n \rightarrow \infty$$

under the null hypothesis H .

PROOF. Note that

$$\begin{aligned} h_n(x) &= n \{ \Gamma_n(F(x)) - F(x) + \Gamma_n(F(2S[\Gamma_n(F)] - x)) - F(2S[\Gamma_n(F)] - x) \\ &\quad + F(2S[\Gamma_n(F)] - x) - F(2m - x) \}^2. \end{aligned}$$

Then we have

$$\begin{aligned} &\sup_x |h_n(x) - h(x)| \\ &\leq \left(\sup_x |n^{1/2}(\Gamma_n(F(x)) - F(x)) - \beta(F(x))| \right. \\ &\quad + \sup_x |n^{1/2}(\Gamma_n(F(2S[\Gamma_n(F)] - x)) - F(2S[\Gamma_n(F)] - x)) \\ &\quad - \beta(F(2S[\Gamma_n(F)] - x))| \\ &\quad + \sup_x |\beta(F(2S[\Gamma_n(F)] - x)) - \beta(F(2m - x))| \\ &\quad + \sup_x \left| n^{1/2}(F(2S[\Gamma_n(F)] - x) - F(2m - x)) \right. \\ &\quad \left. - 2f(2m - x) \int_0^1 S^{(1)}[F: F^{-1}(s)] d\beta(s) \right| \Big) \\ &\quad \times (\sup_x ((h_n(x))^{1/2} + (h(x))^{1/2})). \end{aligned}$$

By Lemma 1 we can see the first and the second terms of the right-hand side converge to zero almost surely. The fourth term converges to zero in probability by the property of Mises functional S . Furthermore it holds that

$$\sup_x ((h_n(x))^{1/2} + (h(x))^{1/2}) = O_p(1).$$

Consequently we have the result of Lemma 2 if the third term is shown to converge to zero in probability. But it is shown by the theorem of Lévy on the sample path of Brownian motion (see Lévy [3] or Hida [2]), i.e. for any constant $c > 1$ and for almost all $\omega \in \Omega$, there exists $\delta = \delta(\omega) > 0$ and if $|t - t'| < \delta$ then

$$|\beta(t', \omega) - \beta(t, \omega)| \leq c \{2|t - t'| \log(1/|t' - t|)\}^{1/2}$$

holds.

For any $\eta > 0$, we will determine $d > 0$ as

$$P\{\omega; \delta(\omega) > d\} \geq 1 - \eta/2.$$

Since $S[F_n]$ converges to m in probability, F is differentiable and the derivative f is bounded, there exists an integer n_0 and

$$P\left\{\sup_x |F(2S[\Gamma_n(F)] - x) - F(2m - x)| < d\right\} \geq 1 - \eta/2 \quad \text{for all } n \geq n_0.$$

By Lévy's theorem it holds that

$$\begin{aligned} & P\left\{\sup_x |\beta(F(2S[\Gamma_n(F)] - x)) - \beta(F(2m - x))|\right. \\ & \quad \leq c\{2\mu|S[\Gamma_n(F)] - m| \log(1/(\mu|2(S[\Gamma_n(F)] - m)|))\}^{1/2} \\ & \quad \left. \geq 1 - \eta \quad \text{for all } n \geq n_0, \text{ where } \mu = \sup_x f(x)\right\}. \end{aligned}$$

Since $S[\Gamma_n(F)] - m$ converges to zero in probability,

$$2\mu|S[\Gamma_n(F)] - m| \log(1/(\mu|2(S[\Gamma_n(F)] - m)|))$$

also converges to zero in probability. Then we have

$$\begin{aligned} & \sup_x |\beta(F(2S[\Gamma_n(F)] - x)) - \beta(F(2m - x))| \rightarrow 0 \\ & \quad \text{in probability as } n \rightarrow \infty. \end{aligned}$$

PROOF OF THEOREM 1. (2.1) is equal to

$$\int_0^1 h_n(F^{-1}(t)) d[\Gamma_n(t) - t].$$

We set $h_n(F^{-1}(t)) = g_n(t)$ and $h(F^{-1}(t)) = g(t)$.

For any function $\phi(t)$ on $[0, 1]$ and for any positive integer k , we define a step function $(\phi)_k(t) = \phi(i/k)$ on $[(i-1)/k, i/k]$, $i = 1, \dots, k$. Then we can easily see the following inequality.

$$\begin{aligned} & \left| \int_0^1 g_n(t) d[\Gamma_n(t) - t] \right| \\ & \leq \left| \int_0^1 (g_n(t) - (g_n)_k(t)) d\Gamma_n(t) \right| + \left| \int_0^1 (g_n(t) - (g_n)_k(t)) dt \right| \end{aligned}$$

$$+ \left| \int_0^1 (g_n)_k(t) d[\Gamma_n(t) - t] \right| .$$

The first term of the right-hand side is estimated as

$$\begin{aligned} & \left| \int_0^1 (g_n(t) - (g_n)_k(t)) d\Gamma_n(t) \right| \\ & \leq \sup_t |g_n(t) - g(t)| + \sup_t |g(t) - (g)_k(t)| + \sup_t |(g)_k(t) - (g_n)_k(t)| \\ & \leq 2 \sup_t |g_n(t) - g(t)| + \sup_t |g(t) - (g)_k(t)| . \end{aligned}$$

Similarly the second term is estimated as

$$\left| \int_0^1 (g_n(t) - (g_n)_k(t)) dt \right| \leq 2 \sup_t |g_n(t) - g(t)| + \sup_t |g(t) - (g)_k(t)| .$$

Note that $\int_a^b d[\Gamma_n(t) - t] = (\Gamma_n(b) - b) - (\Gamma_n(a) - a)$.

Then we have

$$\begin{aligned} & \left| \int_0^1 (g_n)_k(t) d[\Gamma_n(t) - t] \right| \\ & \leq 2k \sup_t |g_n(t)| \sup_t |\Gamma_n(t) - t| \\ & \leq 2k (\sup_t |g_n(t) - g(t)| + \sup_t |g(t)|) \sup_t |\Gamma_n(t) - t| , \end{aligned}$$

where $\sup_t |g(t)| = \sup_x |h(x)| = O_p(1)$.

Fix k sufficiently large so that $\sup_t |g(t) - g_k(t)|$ is sufficiently small.

And let n go to infinity.

Then (2.2) and (2.3) hold:

$$(2.2) \quad \sup_t |g_n(t) - g(t)| \rightarrow 0 \quad \text{in probability as } n \rightarrow \infty \text{ (by Lemma 2) .}$$

$$(2.3) \quad \sup_t |\Gamma_n(t) - t| \rightarrow 0 \quad \text{almost surely as } n \rightarrow \infty \\ \text{(by the Glivenko-Cantelli theorem) .}$$

Therefore we have the desired result.

THEOREM 2. *If Assumptions (A1) and (A2) are satisfied, the asymptotic distribution of (1.2) under the hypothesis H is represented by the following double stochastic integral of a Brownian bridge,*

$$(2.4) \quad \int_0^1 \int_0^1 \phi[F; F^{-1}(u), F^{-1}(v)] d\beta(u) d\beta(v) , \quad \text{where}$$

$$(2.5) \quad \phi[F; y, z] = 2 \int_{-\infty}^{\infty} \chi_{(-\infty, x]}(y) \chi_{(-\infty, x]}(z) dF(x)$$

$$\begin{aligned}
 & + 2 \int_{-\infty}^{\infty} \chi_{(-\infty, 2m-x]}(y) \chi_{(-\infty, x]}(z) dF(x) \\
 & + 2S^{(1)}[F: y] \int_{-\infty}^{\infty} f(x) \{ \chi_{(-\infty, 2m-x]}(z) + \chi_{(-\infty, x]}(z) \} dF(x) \\
 & + 2S^{(1)}[F: z] \int_{-\infty}^{\infty} f(x) \{ \chi_{(-\infty, 2m-x]}(y) + \chi_{(-\infty, x]}(y) \} dF(x) \\
 & + 4 \left\{ \int_{-\infty}^{\infty} (f(2m-x))^2 dF(x) \right\} S^{(1)}[F: y] S^{(1)}[F: z] ,
 \end{aligned}$$

in (2.5) $\chi_A(\cdot)$ denotes the indicator function of A .

Remark. In the first and the second term of the right-hand side of (2.5) we use the change of variables $y = F^{-1}(u)$ and $z = F^{-1}(v)$. Then we can see

$$\begin{aligned}
 & 2 \left\{ \int_{-\infty}^{\infty} \chi_{(-\infty, x]}(y) \chi_{(-\infty, x]}(z) dF(x) \right. \\
 & \quad \left. + \int_{-\infty}^{\infty} \chi_{(-\infty, 2m-x]}(y) \chi_{(-\infty, x]}(z) dF(x) \right\} \\
 & = \begin{cases} 2\{1 - \max(u, v)\} & \text{if } u + v > 1 \\ 2\{2 - \max(u, v) - u - v\} & \text{if } u + v \leq 1. \end{cases}
 \end{aligned}$$

The double stochastic integral of this kernel represents the asymptotic distribution of the test statistic when the center is known (see Filippova [1]). Consequently the other part of the right-hand side of (2.5) is added by estimating the center. And we can see that this part depends on the distribution F and the estimator S .

We can easily prove Theorem 2 by using the following Proposition 1 and Proposition 2.

We define

$$\begin{aligned}
 \bar{T}[F_n] = & \int_{-\infty}^{\infty} \left\{ F_n(x) - F(x) + F_n(2m-x) - F(2m-x) \right. \\
 & \left. + 2f(2m-x) \int_{-\infty}^{\infty} S^{(1)}[F: u] d[F_n(u) - F(u)] \right\}^2 dF(x) .
 \end{aligned}$$

PROPOSITION 1. If Assumptions (A1) and (A2) are satisfied, $nT[F_n]$ and $n\bar{T}[F_n]$ are asymptotically equivalent, i.e.

$$n(T[F_n] - \bar{T}[F_n]) \rightarrow 0 \quad \text{in probability as } n \rightarrow \infty .$$

PROPOSITION 2. If Assumptions (A1) and (A2) are satisfied, it holds that

$$\bar{T}[F_n] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \phi[F: y, z] d[F_n(y) - F(y)] d[F_n(z) - F(z)] .$$

PROOF OF PROPOSITION 1. We set $F_n^{(t)} = (1-t)F + tF_n$ for all $t \in [0, 1]$. In this case

$$T[F_n^{(t)}] = \int_{-\infty}^{\infty} \{(1-t)F(x) + tF_n(x) + (1-t)F(2S[F_n^{(t)}] - x) + tF_n(S[F_n^{(t)}] - x) - 1\}^2 dF(x)$$

is not differentiable with respect to t .

Therefore we define

$$T_1[F_n^{(t)}] = \int_{-\infty}^{\infty} \{(1-t)F(x) + tF_n(x) + (1-t)F(2S[F_n^{(t)}] - x) + ts_n(2S[F_n^{(t)}] - x) - 1\}^2 dF(x),$$

which is differentiable with respect to t , where $s_n(x)$ is the following random function defined for every $\omega \in \Omega$ by

$$s_n(x) = \begin{cases} \frac{i+1}{n} + \frac{\int_{X_{(i)}-1/n^3}^x \exp[1/\{(u-X_{(i)}+1/n^3)(u-X_{(i)})\}] du}{n \int_{X_{(i)}-1/n^3}^{X_{(i)}} \exp[1/\{(u-X_{(i)}+1/n^3)(u-X_{(i)})\}] du} \\ \quad (\text{if } X_{(i)}-1/n^3 \leq x \leq X_{(i)}, i=1, 2, \dots, n) \\ F_n(x) \quad (\text{otherwise}). \end{cases}$$

In the above formula $X_{(1)} \leq \dots \leq X_{(n)}$ denote the order statistics of X_1, \dots, X_n . We define $A_n(x, t)$ by

$$A_n(x, t) = (1-t)F(x) + tF_n(x) + (1-t)F(2S[F_n^{(t)}] - x) - 1.$$

Then it holds that for any real x , for any $t \in [0, 1]$, and for any integer n ,

$$(2.6) \quad |A_n(x, t)| \leq 2.$$

And we have by the definition of $T_1[F_n^{(t)}]$, Schwarz's inequality, and (2.6),

$$\begin{aligned} & |T[F_n^{(t)}] - T_1[F_n^{(t)}]| \\ & \leq \int_{-\infty}^{\infty} |F_n(2S[F_n^{(t)}] - x)|^2 - \{s_n(2S[F_n^{(t)}] - x)\}^2 dF(x) \\ & \quad + \int_{-\infty}^{\infty} 2|A_n(x, t)| \cdot |F_n(2S[F_n^{(t)}] - x) - s_n(2S[F_n^{(t)}] - x)| dF(x) \\ & \leq \left[\int_{-\infty}^{\infty} (F_n(2S[F_n^{(t)}] - x) + s_n(2S[F_n^{(t)}] - x))^2 dF(x) \right]^{1/2} \\ & \quad + 2 \left[\int_{-\infty}^{\infty} |A_n(x, t)|^2 dF(x) \right]^{1/2} \end{aligned}$$

$$\times \left[\int_{-\infty}^{\infty} \{F'_n(2S[F_n^{(\epsilon)}] - x) - s_n(2S[F_n^{(\epsilon)}] - x)\}^2 dF(x) \right]^{1/2}.$$

By the definition of s_n , it holds that $\sup_u |F'_n(u) - s_n(u)| \leq 1/n$ and Lebesgue measure of $\{x; s_n(x) \neq F'_n(x)\} = 1/n^2$. The latter immediately implies F -measure of $\{x; s_n(x) \neq F'_n(x)\} \leq \mu/n^2$, where $\mu = \sup_x f(x)$. Then we have

$$|T[F_n^{(\epsilon)}] - T_1[F_n^{(\epsilon)}]| \leq 6\mu^{1/2}/n^2 \quad \text{for all } t \in [0, 1].$$

Consequently,

$$n(T[F_n^{(\epsilon)}] - T_1[F_n^{(\epsilon)}]) \rightarrow 0 \\ \text{as } n \rightarrow \infty \text{ for all } \omega \in \Omega \text{ and for all } t \in [0, 1].$$

Hence it suffices to investigate the asymptotic distribution of $T_1[F_n^{(\epsilon)}]$. We have (2.7)–(2.11) by differentiating $T_1[F_n^{(\epsilon)}]$ with respect to t .

$$(2.7) \quad \frac{dT_1[F_n^{(\epsilon)}]}{dt} = \int_{-\infty}^{\infty} 2\{(1-t)F(x) + tF'_n(x) + (1-t)F(2S[F_n^{(\epsilon)}] - x) \\ + ts_n(2S[F_n^{(\epsilon)}] - x) - 1\} g(t, x) dF(x),$$

where

$$g(t, x) = F'_n(x) - F(x) - F(2S[F_n^{(\epsilon)}] - x) \\ + 2(1-t)f(2S[F_n^{(\epsilon)}] - x) \frac{dS[F_n^{(\epsilon)}]}{dt} + s_n(2S[F_n^{(\epsilon)}] - x) \\ + 2ts'_n(2S[F_n^{(\epsilon)}] - x) \frac{dS[F_n^{(\epsilon)}]}{dt}.$$

$$(2.8) \quad \left. \frac{dT_1[F_n^{(\epsilon)}]}{dt} \right|_{t=0} = 0.$$

$$(2.9) \quad \frac{d^2 T_1[F_n^{(\epsilon)}]}{dt^2} = \int_{-\infty}^{\infty} 2 \left[\{g(t, x)\}^2 + \{(1-t)F(x) + tF'_n(x) \right. \\ \left. + (1-t)F(2S[F_n^{(\epsilon)}] - x) + ts_n(2S[F_n^{(\epsilon)}] - x) - 1\} \right. \\ \left. \times \frac{dg(t, x)}{dt} \right] dF(x),$$

where

$$\frac{dg(t, x)}{dt} = -4f(2S[F_n^{(\epsilon)}] - x) \frac{dS[F_n^{(\epsilon)}]}{dt} + 4(1-t)f'(2S[F_n^{(\epsilon)}] - x) \\ \times \left\{ \frac{dS[F_n^{(\epsilon)}]}{dt} \right\}^2 + 2(1-t)f(2S[F_n^{(\epsilon)}] - x) \frac{d^2 S[F_n^{(\epsilon)}]}{dt^2} \\ + 4s'_n(2S[F_n^{(\epsilon)}] - x) \frac{dS[F_n^{(\epsilon)}]}{dt} + 4ts''_n(2S[F_n^{(\epsilon)}] - x)$$

$$\times \left\{ \frac{dS[F_n^{(\iota)}]}{dt} \right\}^2 + 2s'_n(2S[F_n^{(\iota)}] - x) \frac{d^2S[F_n^{(\iota)}]}{dt^2} .$$

$$(2.10) \quad \frac{d^2T_1[F_n^{(\iota)}]}{dt^2} \Big|_{t=0} = 2 \int_{-\infty}^{\infty} \{g(0, x)\}^2 dF(x) .$$

$$(2.11) \quad \frac{d^3T_1[F_n^{(\iota)}]}{dt^3} = \int_{-\infty}^{\infty} \left[6g(t, x) \frac{dg(t, x)}{dt} + 2\{(1-t)F(x) + tF_n(x) \right. \\ \left. + (1-t)F(2S[F_n^{(\iota)}] - x) + ts_n(2S[F_n^{(\iota)}] - x) - 1\} \right. \\ \left. \times \frac{d^2g(t, x)}{dt^2} \right] dF(x) ,$$

where

$$\begin{aligned} \frac{d^2g(t, x)}{dt^2} = & -12f'(2S[F_n^{(\iota)}] - x) \left\{ \frac{dS[F_n^{(\iota)}]}{dt} \right\}^2 - 6f(2S[F_n^{(\iota)}] - x) \\ & \times \frac{d^2S[F_n^{(\iota)}]}{dt^2} + 8(1-t)f''(2S[F_n^{(\iota)}] - x) \left\{ \frac{dS[F_n^{(\iota)}]}{dt} \right\}^3 \\ & + 12(1-t)f'(2S[F_n^{(\iota)}] - x) \frac{dS[F_n^{(\iota)}]}{dt} \frac{d^2S[F_n^{(\iota)}]}{dt^2} \\ & + 2(1-t)f(2S[F_n^{(\iota)}] - x) \frac{d^3S[F_n^{(\iota)}]}{dt^3} \\ & + 12s''_n(2S[F_n^{(\iota)}] - x) \left\{ \frac{dS[F_n^{(\iota)}]}{dt} \right\}^2 \\ & + 6s'_n(2S[F_n^{(\iota)}] - x) \frac{d^2S[F_n^{(\iota)}]}{dt^2} \\ & + 8ts_n^{(3)}(2S[F_n^{(\iota)}] - x) \left\{ \frac{dS[F_n^{(\iota)}]}{dt} \right\}^3 \\ & + 12ts''_n(2S[F_n^{(\iota)}] - x) \frac{dS[F_n^{(\iota)}]}{dt} \frac{d^2S[F_n^{(\iota)}]}{dt^2} \\ & + 2ts'_n(2S[F_n^{(\iota)}] - x) \frac{d^3S[F_n^{(\iota)}]}{dt^3} . \end{aligned}$$

By Assumption (A2) and from (2.7), (2.9) and (2.11) we have

$$(2.12) \quad n^{p/2-\delta} \sup_t \left| \frac{d^pT_1[F_n^{(\iota)}]}{dt^p} \right| \rightarrow 0 \quad \text{in probability}$$

for any $\delta > 0$ and $p=1, 2, 3$. Set

$$\begin{aligned} B_n(x) = & F_n(x) - F(x) - F(2m-x) + 2f(2m-x) \\ & \times \int_{-\infty}^{\infty} S^{(1)}[F; u] d[F_n(u) - F(u)] , \end{aligned}$$

then we have

$$(2.13) \quad |B_n(x)| \leq 4 \quad \text{for sufficiently large } n.$$

From the definition of $\bar{T}[F_n]$ and by Schwarz's inequality and (2.13), we have

$$\begin{aligned} & \left| \left(\frac{d^2 T_1[F_n]}{dt^2} \right) \Big|_{t=0} - 2\bar{T}[F_n] \right| \\ & \leq \int_{-\infty}^{\infty} 2|\{s_n(2m-x)\}^2 - \{F_n(2m-x)\}^2| dF(x) \\ & \quad + 4 \int_{-\infty}^{\infty} |B_n(x)| |s_n(2m-x) - F_n(2m-x)| dF(x) \\ & \leq (4+16) \left\{ \int_{-\infty}^{\infty} (s_n(2m-x) - F_n(2m-x))^2 dF(x) \right\}^{1/2} \\ & \leq 20\mu^{1/2}/n^2 \quad \text{for sufficiently large } n. \end{aligned}$$

Consequently we have

$$(2.14) \quad n \left(\frac{d^2 T_1[F_n^{(\epsilon)}]}{dt^2} \Big|_{t=0} - 2\bar{T}[F_n^{(\epsilon)}] \right) \rightarrow 0 \quad \text{as } n \rightarrow \infty \text{ for all } \omega \in \Omega.$$

Let's assume that a functional $R[F_n^{(\epsilon)}]$ is $(m+1)$ times differentiable with respect to t , and

$$(2.15) \quad \frac{d^p R[F_n^{(\epsilon)}]}{dt^p} \Big|_{t=0} = 0, \quad p=1, \dots, m-1,$$

hold. Suppose moreover that

$$(2.16) \quad n^{q/2-\delta} \sup_t \left| \frac{d^q R[F_n^{(\epsilon)}]}{dt^q} \right| \rightarrow 0 \quad \text{in probability as } n \rightarrow \infty$$

for any $\delta > 0$ and $q=1, \dots, m+1$.

If we set $t=1$ on the Taylor expansion for $R[F_n^{(\epsilon)}]$ of order $(m+1)$ at the point $t=0$,

$$\begin{aligned} R[F_n^{(\epsilon)}] &= R[F] + \frac{t}{1!} \frac{dR[F_n^{(\epsilon)}]}{dt} \Big|_{t=0} + \dots + \frac{t^m}{m!} \frac{d^m R[F_n^{(\epsilon)}]}{dt^m} \Big|_{t=0} \\ & \quad + \frac{t^{m+1}}{(m+1)!} \frac{d^{m+1} R[F_n^{(\epsilon)}]}{dt^{m+1}} \Big|_{t=\theta}, \end{aligned}$$

then we have by (2.15)

$$(2.17) \quad R[F_n] - R[F] - \frac{1}{m!} \frac{d^m R[F_n^{(\epsilon)}]}{dt^m} \Big|_{t=0} = \frac{1}{(m+1)!} \frac{d^{m+1} R[F_n^{(\epsilon)}]}{dt^{m+1}} \Big|_{t=\theta'}.$$

Then (2.16) implies

$$(2.18) \quad n^{m/2} (R[F_n] - R[F]) - \frac{n^{m/2}}{m!} \frac{d^m R[F_n^{(\epsilon)}]}{dt^m} \Big|_{t=0} \rightarrow 0 \quad \text{in probability.}$$

By (2.7)–(2.12), $T_1[F_n^{(\epsilon)}]$ satisfies (2.15) and (2.16) with $m=2$. Therefore we have

$$(2.19) \quad nT_1[F_n] - \frac{n}{2!} \frac{d^2 T_1[F_n^{(\epsilon)}]}{dt^2} \Big|_{t=0} \rightarrow 0 \quad \text{in probability as } n \rightarrow \infty.$$

Proposition 1 now follows from (2.14) and (2.19).

PROOF OF PROPOSITION 2. By the definition of $\bar{T}[F_n]$ we have

$$\begin{aligned} \bar{T}[F_n] = & \int_{-\infty}^{\infty} \{F_n(x) - F(x)\}^2 dF(x) + \int_{-\infty}^{\infty} \{F_n(2m-x) - F(2m-x)\}^2 dF(x) \\ & + 4 \left\{ \int_{-\infty}^{\infty} S^{(1)}[F: u] d[F_n(u) - F(u)] \right\}^2 \int_{-\infty}^{\infty} f^2(2m-x) dF(x) \\ & + 2 \int_{-\infty}^{\infty} \{F_n(x) - F(x)\} \{F_n(2m-x) - F(2m-x)\} dF(x) \\ & + 4 \int_{-\infty}^{\infty} S^{(1)}[F: u] d[F_n(u) - F(u)] \\ & \times \int_{-\infty}^{\infty} \{F_n(x) - F(x)\} f(2m-x) dF(x) \\ & + 4 \int_{-\infty}^{\infty} S^{(1)}[F: u] d[F_n(u) - F(u)] \\ & \times \int_{-\infty}^{\infty} \{F_n(2m-x) - F(2m-x)\} f(2m-x) dF(x). \end{aligned}$$

The result of Proposition 2 is shown by the following calculations (2.20)–(2.24).

$$\begin{aligned} (2.20) \quad & \int_{-\infty}^{\infty} \{F_n(x) - F(x)\}^2 dF(x) \\ & = \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} (F_n(x) - F(x)) \chi_{(-\infty, x]}(z) dF(x) \right\} d[F_n(z) - F(z)] \\ & = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} \chi_{(-\infty, x]}(y) \chi_{(-\infty, x]}(z) dF(x) \right\} \\ & \quad \times d[F_n(y) - F(y)] d[F_n(z) - F(z)]. \end{aligned}$$

$$\begin{aligned} (2.21) \quad & \int_{-\infty}^{\infty} \{F_n(2m-x) - F(2m-x)\}^2 dF(x) \\ & = \int_{-\infty}^{\infty} \{F_n(y) - F(y)\}^2 dF(y) \\ & = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} \chi_{(-\infty, x]}(y) \chi_{(-\infty, x]}(z) dF(x) \right\} \\ & \quad \times d[F_n(y) - F(y)] d[F_n(z) - F(z)]. \end{aligned}$$

$$(2.22) \quad \int_{-\infty}^{\infty} \{F_n(2m-x) - F(2m-x)\} \{F_n(x) - F(x)\} dF(x)$$

$$\begin{aligned}
 &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} \chi_{(-\infty, 2m-x]}(z) \chi_{(-\infty, x]}(y) dF(x) \right\} \\
 &\quad \times d[F_n(y) - F(y)] d[F_n(z) - F(z)] . \\
 (2.23) \quad &\int_{-\infty}^{\infty} S^{(1)}[F: u] d[F_n(u) - F(u)] \int_{-\infty}^{\infty} \{F_n(x) - F(x)\} f(2m-x) dF(x) \\
 &= \int_{-\infty}^{\infty} S^{(1)}[F: u] d[F_n(u) - F(u)] \\
 &\quad \times \int_{-\infty}^{\infty} \left(\int_{-\infty}^{\infty} f(2m-x) \chi_{(-\infty, x]}(z) dF(x) \right) d[F_n(z) - F(z)] \\
 &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[\left\{ \int_{-\infty}^{\infty} \chi_{(-\infty, x]}(z) f(2m-x) dF(x) \right\} S^{(1)}[F: y] \right] \\
 &\quad \times d[F_n(y) - F(y)] d[F_n(z) - F(z)] . \\
 (2.24) \quad &\int_{-\infty}^{\infty} S^{(1)}[F: u] d[F_n(u) - F(u)] \\
 &\quad \times \int_{-\infty}^{\infty} \{F_n(2m-x) - F(2m-x)\} f(2m-x) dF(x) \\
 &= \int_{-\infty}^{\infty} S^{(1)}[F: u] d[F_n(u) - F(u)] \int_{-\infty}^{\infty} \{F_n(x) - F(x)\} f(x) dF(x) \\
 &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[\left\{ \int_{-\infty}^{\infty} f(x) \chi_{(-\infty, x]}(z) dF(x) \right\} S^{(1)}[F: y] \right] \\
 &\quad \times d[F_n(y) - F(y)] d[F_n(z) - F(z)] .
 \end{aligned}$$

By Theorem 1 and Theorem 2 we can conclude that the asymptotic distribution of $nT_0[F_n]$ under the hypothesis H is equal to the distribution of the double stochastic integral defined by (2.4).

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