

## ON FIXED SIZE CONFIDENCE BANDS FOR THE BUNDLE STRENGTH OF FILAMENTS<sup>1</sup>

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The present paper deals with the asymptotic theory of sequential confidence intervals of prescribed width  $2d$  ( $d > 0$ ) and prescribed coverage probability  $1 - \alpha$  ( $0 < \alpha < 1$ ) for the (unknown, per unit) strength of bundle of parallel filaments. In this context, certain useful convergence results on the empirical distribution and on the bundle strength of filaments are established and incorporated in the proofs of the main theorems. The results are the sequential counterparts of some fixed sample size results derived in a concurrent paper of Sen, Bhattacharyya and Suh [9].

**1. Introduction and summary.** For fixed (but large) sample sizes, the distribution theory of bundle strength of filaments has been studied by Daniels [4], Sen, Bhattacharyya and Suh [9], and others. The object of the present investigation is to develop, along the lines of Anscombe [1] and Chow and Robbins [3], the asymptotic theory of bounded length sequential confidence intervals for the bundle strength of filaments.

Let  $\{X_i, i \geq 1\}$  be a sequence of independent and identically distributed (i.i.d.) nonnegative random variables (rv) defined on a probability space  $(\Omega, \mathcal{A}, P)$ . We assume that  $X_i$  has an absolutely continuous cumulative distribution function (cdf)  $F(x)$ ,  $x \in [0, \infty)$ , with a continuous first derivative (density function)  $f(x)$ , such that

$$(1.1) \quad 0 < \lambda^2 = \int_0^\infty x^2 dF(x) < \infty,$$

and there exists a unique  $x_0$  (a point of continuity of  $f(x)$ ), for which

$$(1.2) \quad \theta = \sup_{x \geq 0} \{x[1 - F(x)]\} = x_0[1 - F(x_0)] \quad \text{and} \quad 0 < \pi_0 = F(x_0) < 1.$$

Note that

$$(1.3) \quad 0 < \theta < \int_0^\infty x dF(x) < \lambda; \quad 0 < x_0 < \infty,$$

and the derivative of  $x[1 - F(x)]$  vanishes at  $x = x_0$ , so that  $f(x_0) > 0$ . Further, we assume that there exist four positive constants  $C_1$ ,  $C_2$  and  $k_1 (> 1)$ ,  $k_2 (> 1)$ , such that for sufficiently small  $\delta (> 0)$ ,

$$(1.4) \quad \theta - C_1|x - x_0|^{k_1} \leq x[1 - F(x)] \leq \theta - C_2|x - x_0|^{k_2} \\ \text{for all } |x - x_0| \leq \delta.$$

In fact, if  $x[1 - F(x)]$  is twice differentiable in some neighborhood of  $x_0$  and the second derivative does not vanish there, then (1.4) holds with  $k_1 = k_2 = 2$ .

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Our parameter of interest is  $\theta$ . For a random sample  $X_1, \dots, X_n$  of size  $n$  from the distribution  $F(x)$ , we denote the ordered random variables by  $X_{n,1} \leq \dots \leq X_{n,n}$ . Let then

$$(1.5) \quad D_n = \max_{1 \leq i \leq n} [(n - i + 1)X_{n,i}] = (n - r_n + 1)X_{n,r_n} \quad \text{and} \\ Z_n = n^{-1}D_n ;$$

by virtue of the assumed continuity of  $F(x)$  and (1.2),  $r_n$  (a random variable assuming only integer values between 1 and  $n$ ) is unique, with probability one. It is shown in [9] that  $Z_n$  converges to  $\theta$  almost surely (a.s.) as  $n \rightarrow \infty$ . When the  $X_i$  represent the breaking stresses of filaments,  $D_n$  is equal to the maximum stress which a bundle of  $n$  parallel filaments of equal length can stand, and is termed the bundle strength (cf. [4], [9]). We term  $\theta$  as the *mean (per unit) bundle strength of filaments*. We want to find a confidence interval for  $\theta$  of prescribed width  $2d$ ,  $d > 0$ , and prescribed confidence coefficient  $\gamma$  ( $0 < \gamma < 1$ ). Since, neither  $F(x)$  nor the distribution of  $D_n$  is explicitly known, no fixed sample size procedure sounds available.

For  $n \geq 1$ , we define

$$(1.6) \quad I_n(d) = [Z_n - d, Z_n + d], \quad d > 0, \quad \text{and} \quad p_n = (n + 1)^{-1}r_n .$$

Also, let  $\{a_n\}$  be a sequence of known positive constants such that

$$\lim_{n \rightarrow \infty} a_n = a \quad \text{where} \quad (2\pi)^{-\frac{1}{2}} \int_{-a}^a \exp(-2^{-1}t^2) dt = \gamma .$$

Finally, let

$$(1.7) \quad v_n(d) = a_n^2 Z_n^2 p_n / [d^2(1 - p_n)] \quad \text{and} \quad \nu(d) = a^2 \theta^2 \pi_0 / [d^2(1 - \pi_0)] .$$

Then, our proposed sequential confidence interval  $I_{N(d)}(d) = \{\theta : Z_{N(d)} - d < \theta < Z_{N(d)} + d\}$  is based on the stopping (random) variable  $N(d)$ , defined by

$$(1.8) \quad N(d) = \text{first positive integer } n (\geq 2) \text{ for which } v_n(d) \leq n .$$

The following theorems establish the properties of  $N(d)$  and  $I_{N(d)}$ .

**THEOREM 1.1.** *If  $\lambda < \infty$ , then for every  $d > 0$ , the sequential procedure terminates with probability one. In fact, there exists a  $t_0 (= t_0(d) > 0$  for  $d > 0$ ), such that*

$$(1.9) \quad E\{\exp [tN(d)]\} < \infty \quad \text{for every} \quad -\infty < t \leq t_0 .$$

**THEOREM 1.2.** *Under (1.1) through (1.4),  $N(d)$  is a non-increasing functions of  $d$  ( $> 0$ ),  $\lim_{d \rightarrow 0} N(d) = \infty$  a.s., and  $\lim_{d \rightarrow 0} E[N(d)] = \infty$ ;*

$$(1.10) \quad \lim_{d \rightarrow 0} \{N(d)/\nu(d)\} = 1 \quad \text{a.s.}, \quad \lim_{d \rightarrow 0} P\{\theta \in I_{N(d)}(d)\} = \gamma ,$$

$$(1.11) \quad \lim_{d \rightarrow 0} \{E[N(d)]/\nu(d)\} = 1 .$$

The proofs of the theorems are postponed to Section 4. It may be noted that the estimator  $Z_n$  of  $\theta$  or  $v_n(d)$  of  $\nu(d)$  is not linear in  $X_i$  or  $X_i^2$  etc., and hence, the results of Anscombe [1] or of Chow and Robbins [3] are not directly applicable. In fact, we need to prove some a.s. convergence results on  $\{Z_n\}$  (see

Section 3) for the validation of the condition of 'uniform continuity in probability' (with respect to  $n^{-\frac{1}{2}}$ ) of Anscombe [1] (also implicit in [3]). This, in turn, requires certain convergence results on the empirical cdf which are studied in Section 2. The last section develops sequential fixed percentage error confidence bands for  $\theta$ .

**2. Some results on the empirical cdf.** Let  $c(u)$  be equal to 1 or 0 according as  $u$  is  $> 0$  or not. Define the empirical cdf  $F_n(x)$  by

$$(2.1) \quad F_n(x) = n^{-1} \sum_{i=1}^n c(x - X_i), \quad 0 \leq x < \infty.$$

By the Glivenko–Cantelli Theorem, we know that

$$(2.2) \quad \sup_x |F_n(x) - F(x)| \rightarrow 0 \quad \text{a.s.}, \quad \text{as } n \rightarrow \infty.$$

Also, by the well-known results on the Kolmogorov–Smirnov statistics, we know that for every  $\varepsilon > 0$ , there exists a positive  $K_\varepsilon (< \infty)$ , such that for every  $n \geq 1$ ,

$$(2.3) \quad P\{\sup_x n^{\frac{1}{2}} |F_n(x) - F(x)| > K_\varepsilon\} < \varepsilon;$$

in fact, by Lemma 2 of Dvoretzky, Kiefer and Wolfowitz [5], we obtain that for every  $n \geq 1$  and  $r \geq 0$ ,

$$(2.4) \quad P\{\sup_x n^{\frac{1}{2}} |F_n(x) - F(x)| > r\} \leq c\{\exp[-2r^2]\}, \quad \text{where } 0 < c < \infty,$$

and hence,

$$(2.5) \quad \sup_x |F_n(x) - F(x)| \leq n^{-\frac{1}{2}}(\log n)^{\frac{1}{2}} \quad \text{a.s.}, \quad \text{as } n \rightarrow \infty.$$

**THEOREM 2.1.** *If  $\lambda < \infty$ , then for every  $\varepsilon > 0$ , there exist positive constants  $C (< \infty)$ ,  $\rho(\varepsilon) : 0 < \rho(\varepsilon) < 1$ , and an integer  $n_0(\varepsilon)$ , such that for  $n \geq n_0(\varepsilon)$ ,*

$$(2.6) \quad P\{\sup_{0 \leq x < \infty} x |F_n(x) - F(x)| > \varepsilon\} \leq C[\rho(\varepsilon)]^n,$$

and hence,

$$(2.7) \quad \sup_{0 \leq x < \infty} x |F_n(x) - F(x)| \rightarrow 0 \quad \text{a.s.}, \quad \text{as } n \rightarrow \infty.$$

**PROOF.** If the range of the cdf  $F$  is finite, i.e.,  $F(a) = 1$  for some  $a < \infty$ , then noting that  $F_n(x) = F(x) = 1$  for all  $x \geq a$ , so that

$$(2.8) \quad \sup_{0 \leq x < \infty} x |F_n(x) - F(x)| = \sup_{0 \leq x \leq a} x |F_n(x) - F(x)| \\ \leq a[\sup_x |F_n(x) - F(x)|],$$

the result directly follows from (2.4). Hence, in the sequel, it will be assumed that  $F(x) < 1$  for all  $x < \infty$ .

Note that  $\lambda < \infty \Rightarrow x^2[1 - F(x)]$  converges to 0 as  $x \rightarrow \infty$ . Hence, for every  $\varepsilon > 0$ , there exists a positive  $K_\varepsilon$  ( $x_0 < K_\varepsilon < \infty$ ), such that

$$(2.9) \quad \sup_{x \leq K_\varepsilon} x[1 - F(x)] = \theta, \quad \sup_{x > K_\varepsilon} x[1 - F(x)] \leq \theta - 2\varepsilon;$$

$$(2.10) \quad \inf_{x \geq K_\varepsilon} \{[1 - F(x) + \varepsilon/2x] \log(1 + \varepsilon/2x[1 - F(x)])\} \geq 2\varepsilon.$$

Also,

$$(2.11) \quad \sup_x \{x |F_n(x) - F(x)|\} \\ = \max \{\sup_{x \leq K_\varepsilon} x |F_n(x) - F(x)|, \sup_{x > K_\varepsilon} x |F_n(x) - F(x)|\},$$

Thus, it suffices to show that for  $n \geq n_0(\epsilon)$ ,

$$(2.12) \quad P\{\sup_{x \leq K_\epsilon} x|F_n(x) - F(x)| > \epsilon\} \leq C_1[\rho(\epsilon)]^n,$$

$$(2.13) \quad P\{\sup_{x \geq K_\epsilon} x|F_n(x) - F(x)| > \epsilon\} \leq C_2[\rho(\epsilon)]^n,$$

where  $C_1$  and  $C_2$  are positive (finite) constants. Now, as in (2.8), (2.12) follows from (2.4), so we need only to prove (2.13). For this define

$$(2.14) \quad b_j^{(n)} = K_\epsilon + jn^{-1}, \quad j = 0, \dots, n^* = [\exp(\epsilon'n)]; \quad 0 < \epsilon' < \epsilon/2.$$

Then,

$$(2.15) \quad P\{\sup_{x \geq K_\epsilon} x|F_n(x) - F(x)| > \epsilon\} \leq P\{\sup_{K_\epsilon \leq x \leq b_{n^*}^{(n)}} x|F_n(x) - F(x)| > \epsilon\} \\ + P\{\sup_{x > b_{n^*}^{(n)}} x|F_n(x) - F(x)| > \epsilon\},$$

where the second term on the right-hand side of (2.15) is bounded from above by

$$(2.16) \quad P\{\sup_{x > b_{n^*}^{(n)}} x|F_n(x) - F(x)| > \epsilon, \max_{1 \leq i \leq n} X_i \leq b_{n^*}^{(n)}\} \\ + P\{\max_{1 \leq i \leq n} X_i > b_{n^*}^{(n)}\}.$$

If  $X_1, \dots, X_n$  are all  $\leq b_{n^*}^{(n)}$ , for  $x \geq b_{n^*}^{(n)}$ ,  $x|F_n(x) - F(x)| = x[1 - F(x)]$ , and as  $x^2[1 - F(x)] \rightarrow 0$  with  $x \rightarrow \infty$ , for every  $\epsilon > 0$ , there exists an  $n_0(\epsilon)$ , such that for  $n \geq n_0(\epsilon)$ ,  $x[1 - F(x)] < \epsilon$  for every  $x > b_{n^*}^{(n)}$ . Consequently, the first term of (2.16) vanishes for every  $n \geq n_0(\epsilon)$ . On the other hand, by (2.14) and the fact that as  $x \rightarrow \infty$ ,  $x^2[1 - F(x)] \rightarrow 0$ , the second term can be expressed as

$$(2.17) \quad 1 - [F(b_{n^*}^{(n)})]^n = 1 - \{1 - [1 - F(b_{n^*}^{(n)})]\}^n \\ \leq 1 - \{1 - o([b_{n^*}^{(n)}]^{-2})\}^n \\ = o[\exp(-2\epsilon'n + \log n)] \\ = o[\exp(-\epsilon'n)], \quad \text{for } n \geq n_0(\epsilon).$$

Thus, it suffices to show that

$$(2.18) \quad P\{\sup_{K_\epsilon \leq x \leq b_{n^*}^{(n)}} x|F_n(x) - F(x)| > \epsilon\} \leq C_2'[\rho(\epsilon)]^n; \quad 0 < C_2' < \infty.$$

In the choice of  $K_\epsilon$  in (2.9) and (2.10), we may let (without any loss of generality)  $K_\epsilon \geq 1$ , so that by (2.14),  $b_{j+1}^{(n)}/b_j^{(n)} \leq 1 + n^{-1}$ , for every  $j \geq 0$ . Then, for  $x \in [b_j^{(n)}, b_{j+1}^{(n)}]$ ,

$$(2.19) \quad x|F_n(x) - F(x)| \leq (1 + n^{-1})\{\max[U_{nj}, U_{n(j+1)}] + b_j^{(n)}[F(b_{j+1}) - F(b_j^{(n)})]\},$$

where

$$(2.20) \quad U_{nj} = b_j^{(n)}[F_n(b_j^{(n)}) - F(b_j^{(n)})], \quad j \geq 0.$$

Note that for  $j \geq 0$ ,

$$(2.21) \quad b_j^{(n)}[F(b_{j+1}^{(n)}) - F(b_j^{(n)})] \leq \int_{b_j^{(n)}}^{b_{j+1}^{(n)}} x dF(x) \\ \leq [\int_{b_j^{(n)}}^{b_{j+1}^{(n)}} x^2 dF(x)]/b_j^{(n)} \rightarrow 0 \quad \text{as } n \rightarrow \infty, \\ \text{by (1.1) and (2.14),}$$

and hence, for (2.18), it suffices to show that for every  $\epsilon > 0$ , there exist an  $n_0(\epsilon)$  and a  $\rho(\epsilon) : 0 < \rho(\epsilon) < 1$ , such that for  $n \geq n_0(\epsilon)$ ,

$$(2.22) \quad P\{\max_{0 \leq j \leq b_{n^*}} |U_{nj}| > \epsilon/2\} \leq C_2'[\rho(\epsilon)]^n .$$

Note that  $U_{nj} = (1/n) \sum_{i=1}^n \{b_j^{(n)}[c(b_j^{(n)} - X_i) - F(b_j^{(n)})]\} = n^{-1} \sum_{i=1}^n d_{nij}$ , where  $d_{nij}, i = 1, \dots, n$ , are i.i.d. bounded rv's with mean 0 and  $-b_j^{(n)}F(b_j^{(n)}) \leq d_{nij} \leq b_j^{(n)}[1 - F(b_j^{(n)})]$ . Thus, by Theorem 3 of Hoeffding [6],

$$(2.23) \quad \begin{aligned} P\{U_{nj} < -\epsilon/2\} &\leq \{(1 + \epsilon/2x[1 - F(x)])^{1-F(x)+\epsilon/2x}(1 - \epsilon/2xF(x))^{xF(x)-\epsilon/2}\}^{-n} \Big|_{x=b_j^{(n)}} \\ &\leq \exp(-\epsilon n) , \end{aligned}$$

as for  $x \geq K_\epsilon$ , by (2.9) and (2.10),  $[1 - F(x) + \epsilon/2x] \log(1 + \epsilon/2x[1 - F(x)]) + (xF(x) - \epsilon/2) \log(1 - \epsilon/2xF(x)) \geq \epsilon$ . In a similar manner, it follows that

$$(2.24) \quad P\{U_{nj} > \epsilon/2\} \leq \exp(-\epsilon n) \quad \text{for } n \geq n_0(\epsilon) .$$

Consequently, by (2.23), (2.24) and the Bonferroni inequality, for  $n \geq n_0(\epsilon)$ ,

$$(2.25) \quad \begin{aligned} P\{\max_{0 \leq j \leq n^*} |U_{nj}| > \epsilon/2\} &\leq 2(n^* + 1)[\exp(-\epsilon n)] \simeq 2[\exp(-\epsilon n + \epsilon' n)] \\ &\leq 2[\exp(-\epsilon n/2) = 2[\exp(-\epsilon/2)]^n , \end{aligned}$$

and hence, the proof of (2.6) is complete. (2.7) follows directly from (2.6) and the Borel-Cantelli lemma.  $\square$

REMARK. When the  $X_i$  are real valued rv's, defined over  $(-\infty, \infty)$ , the theorem readily extends with the range of  $x$  as  $(-\infty, \infty)$ . Further, if the  $X_i$  are independent but not necessarily identically distributed, we denote the cdf of  $X_i$  by  $F_i^*(x)$  and let  $\bar{F}_n^* = n^{-1} \sum_{i=1}^n F_i^*$ ,  $n \geq 1$ . If then,

$$(2.26) \quad \sup_n \int_0^\infty x^2 d\bar{F}_n^*(x) < \lambda^2 < \infty ,$$

the conclusions of Theorem 2.1 hold with  $F$  replaced by  $\bar{F}_n^*$ .

Now, by (2.3) and (2.5), for every  $K_\epsilon (< \omega)$ ,

$$(2.27) \quad \sup_{0 \leq x \leq K_\epsilon} n^\frac{1}{2}|x[F_n(x) - F(x)]| = O_p(1) ,$$

$$(2.28) \quad \sup_{0 \leq x \leq K_\epsilon} n^\frac{1}{2}|x[F_n(x) - F(x)]| = O((\log n)^\frac{1}{2}) \quad \text{a.s.}, \quad \text{as } n \rightarrow \infty .$$

Let us then write

$$(2.29) \quad a_{n,\alpha} = n^{-\alpha} \log n , \quad A(n, \alpha) = [x_0 - a_{n,\alpha}, x_0 + a_{n,\alpha}] ,$$

$$(2.30) \quad G_n(x_0, \alpha) = \sup \{n^\frac{1}{2}|[F_n(x) - F(x)] - [F_n(x_0) - F(x_0)]| : x \in A(n, \alpha)\} .$$

THEOREM 2.2. For any  $\alpha : 0 < \alpha < 1$ , as  $n \rightarrow \infty$

$$(2.31) \quad G_n(x_0, \alpha) = O(n^{-\alpha/2} \log n) , \quad \text{with probability } 1 .$$

PROOF. We consider  $2n^\beta$  ( $\beta \leq \frac{1}{2}$ ) equidistant points on  $A(n, \alpha)$  and apply the same technique as in Lemma 1 of Bahadur [2], who considered the special case  $\alpha = \frac{1}{2}$ ; for brevity, the details are omitted. Further, if the distributions are not all the same, we can proceed as in Sen [8] and derive the same result (on replacing  $F$  by  $\bar{F}_n^*$ ).

Let us now define

$$(2.32) \quad M_n = n^{\frac{1}{2}}\{x_0[F_n(x_0) - F(x_0)]\} \quad \text{and} \quad \zeta^2 = x_0^2\pi_0(1 - \pi_0).$$

**THEOREM 2.3.** *For every positive  $\varepsilon$  and  $\eta$ , there exists a  $\delta (> 0)$ , such that for all  $n \geq n_0(\varepsilon, \eta)$  and  $N \leq \delta n$*

$$(2.23) \quad P\{\sup_{1 \leq j \leq N} |M_n - M_{n+j}| > \varepsilon \zeta\} < \eta.$$

**PROOF.** From (2.1) and (2.32), it follows that  $M_n^* = n^{\frac{1}{2}}M_n$  forms a martingale sequence, and hence, by the well-known Kolmogorov inequality

$$(2.34) \quad P\{\sup_{1 \leq j \leq N} |M_{n+j}^*| > t_1\} \leq t_1^{-2}E\{M_{n+N}^*\}^2 \leq n(1 + \delta)(\zeta/t_1)^2,$$

for all  $N \leq \delta n$ . Also, for all  $1 \leq j \leq N \leq \delta n$ ,

$$(2.35) \quad |M_{n+j} - M_n| = |(n + j)^{-\frac{1}{2}}M_{n+j}^* - n^{-\frac{1}{2}}M_n^*| \\ \leq n^{-\frac{1}{2}}\{|M_{n+j}^* - M_n^*| + [((1 + \delta)^{\frac{1}{2}} - 1)/(1 + \delta)^{\frac{1}{2}}]|M_n^*|\}.$$

Hence, it follows from (2.34) and (2.35) that we are only to show that for every positive  $\varepsilon'$  ( $< \varepsilon$ ) and  $\eta'$  ( $< \eta$ ), there exists a  $\delta (> 0)$  such that

$$(2.36) \quad P\{\sup_{1 \leq j \leq N} |M_{n+j}^* - M_n^*| > n^{\frac{1}{2}}\zeta\varepsilon'\} < \eta' \quad \text{for all } N \leq \delta n$$

and this readily follows from the Kolmogorov inequality on martingales (cf. [7], page 386).

**3. Convergence of  $Z_n$  and  $p_n$ .** We are mainly interested in the following theorems.

**THEOREM 3.1.** *If  $\lambda < \infty$ , then for every  $\varepsilon > 0$ , there exist a positive integer  $n_0(\varepsilon)$  and a  $\rho(\varepsilon): 0 < \rho(\varepsilon) < 1$ , such that for  $n \geq n_0(\varepsilon)$ ,*

$$(3.1) \quad P\{|Z_n - \theta| > \varepsilon\} \leq [\rho(\varepsilon)]^n.$$

**PROOF.** By (1.5) and (2.1), we have

$$(3.2) \quad Z_n = [1 - F_n(X_{n,r_n})] = \sup_{x \geq 0} \{x[1 - F_n(x)]\},$$

and by assumption,

$$(3.3) \quad \theta = x_0[1 - F(x_0)] = \sup_{x \geq 0} \{x[1 - F(x)]\}.$$

Also, (3.2), (3.3) and the event that  $\sup_x |x[F_n(x) - F(x)]| < \varepsilon$  imply that

$$|Z_n - \theta| = |\sup_x x[1 - F(x)] - \sup_x x[1 - F_n(x)]| \leq \sup_x |x[F_n(x) - F(x)]| \leq \varepsilon.$$

Hence, the proof directly follows from Theorem 2.1.  $\square$

Note that (3.1) implies that

$$(3.4) \quad [\lambda < \infty] \Rightarrow Z_n \rightarrow \theta \quad \text{a.s.}, \quad \text{as } n \rightarrow \infty.$$

For our purposes, we require some relatively stronger results, stated below.

**THEOREM 3.2.** *Under (1.1)—(1.4),  $[n^{\frac{1}{2}}(Z_n - \theta) + M_n] \rightarrow 0$ , with probability one, as  $n \rightarrow \infty$ .*

PROOF. Since  $x[1 - F(x)]$  has a unique maximum  $\theta$  at  $x_0$ , for every (small)  $\varepsilon > 0$ , there exists a  $\delta (> 0)$ , such that

$$(3.5) \quad x[1 - F(x)] \leq \theta - 2\varepsilon \quad \text{for all } |x - x_0| > \delta.$$

Thus, by (2.7), (3.3) and (3.5),

$$(3.6) \quad \sup \{x[1 - F_n(x)]: |x - x_0| > \delta\} \leq \theta - \varepsilon, \quad \text{with probability 1,} \\ \text{as } n \rightarrow \infty.$$

With the definition of  $k_2$  in (1.4), we let  $\alpha = 1/2k_2$  in (2.29), and let

$$(3.7) \quad \tilde{A}(n, \alpha) = [x_0 - \delta, x_0 + \delta] - A(n, \alpha).$$

Then, for all  $x \in A(n, \alpha)$

$$(3.8) \quad \sup \{|n^{\frac{1}{2}}\{x[1 - F_n(x)] - x[1 - F(x)]\} + M_n|: x \in A(n, \alpha)\} \\ = \sup \{|(x_0 - x)n^{\frac{1}{2}}[F_n(x) - F(x)] + x_0 G_n(x, \alpha)|: x \in A(n, \alpha)\} + o(n^{-\frac{1}{2}}) \\ = O(n^{-\alpha/2}[\log n]), \quad \text{with probability 1,} \quad \text{as } n \rightarrow \infty,$$

by virtue of Theorem 2.2, (2.27) and (2.29). Consequently,

$$(3.9) \quad n^{\frac{1}{2}}[\sup \{x[1 - F_n(x)]: x \in A(n, \alpha)\} - \theta] + M_n = O(n^{-\alpha/2}(\log n)),$$

with probability 1, as  $n \rightarrow \infty$ . Finally, by (2.28), as  $n \rightarrow \infty$ ,

$$(3.10) \quad \sup \{|x[F_n(x) - F(x)]|: x \in \tilde{A}(n, \alpha)\} = O(n^{-\frac{1}{2}}(\log n)^{\frac{1}{2}}),$$

with probability 1, and by (1.4) and the value of  $\alpha = 1/(2k_2)$ ,

$$(3.11) \quad \sup \{x[1 - F(x)]: x \in \tilde{A}(n, \alpha)\} \leq \theta - O([n^{-\frac{1}{2}}(\log n)^{k_2}]).$$

Upon noting that for large  $n$ ,  $O(n^{-\frac{1}{2}}(\log n)^{\frac{1}{2}}) = o(1)O(n^{-\frac{1}{2}}(\log n)^k)$  for all  $k \geq 1$ , it follows from (3.10) and (3.11) that

$$(3.12) \quad \sup \{x[1 - F_n(x)]: x \in \tilde{A}(n, \alpha)\} \leq \theta - O([n^{-\frac{1}{2}}(\log n)^{k_2}]), \\ \text{with probability 1.}$$

Since, by (2.27) and (2.32),  $|M_n| \leq x_0(\log n)^{\frac{1}{2}}$ , with probability 1 (as  $n \rightarrow \infty$ ), it follows from (3.6), (3.9) and (3.12) that as  $n \rightarrow \infty$ ,

$$(3.13) \quad W_n = n^{\frac{1}{2}}(Z_n - \theta) + M_n \rightarrow 0, \quad \text{with probability 1. } \square$$

Now, from (3.13), it follows that for every  $\varepsilon > 0$ , there exists an  $\eta > 0$ , such that for all  $n \geq n_0(\varepsilon, \eta)$

$$(3.14) \quad P\{|W_{n+j}| > \varepsilon \text{ for at least one } j = 1, \dots, N, \dots\} < \eta.$$

Hence, from Theorem 2.3, Theorem 3.2 and (3.14), we arrive at the following.

**THEOREM 3.3.** *For every positive  $\varepsilon$  and  $\eta$  there exists a  $\delta > 0$ , such that for all  $n \geq n_0(\varepsilon, \eta)$  and  $N \leq \delta n$*

$$(3.15) \quad P\{|Z_{n+j} - Z_n| < n^{-\frac{1}{2}}\zeta\varepsilon \text{ for all } j = 1, \dots, N\} \geq 1 - \eta.$$

Further, we state the following result already proved in [4], [9]: for every  $t$ ,

$$(3.16) \quad \lim_{n \rightarrow \infty} P\{n^{\frac{1}{2}}(Z_n - \theta)/\zeta \leq t\} = (2\pi)^{-\frac{1}{2}} \int_{-\infty}^t \exp(-\frac{1}{2}x^2) dx, \quad -\infty < t < \infty.$$

**THEOREM 3.4.** *If  $\lambda < \infty$ , for every  $\varepsilon > 0$ , there exist an  $n_0(\varepsilon)$  and a  $\rho(\varepsilon) : 0 < \rho(\varepsilon) < 1$ , such that for  $n \geq n_0(\varepsilon)$ ,*

$$(3.17) \quad P\{p_n < \pi_0 - \varepsilon\} \leq 2[\rho(\varepsilon)]^n \quad \text{and} \quad P\{p_n > \pi_0 + \varepsilon\} \leq 2[\rho(\varepsilon)]^n.$$

**PROOF.** We only prove the result for  $p_n > \pi_0 + \varepsilon$ , as the same proof holds for the other case. Corresponding to every  $\varepsilon > 0$ , we can find an  $\eta (> 0)$  such that  $F(x_0 + \eta) = \pi_0 + \varepsilon/2$ . Then, we have

$$(3.18) \quad \begin{aligned} P\{p_n > \pi_0 + \varepsilon\} &= P\left\{\frac{n}{n+1} F_n(X_{n,r_n}) > \pi_0 + \varepsilon\right\} \\ &\leq P\{F_n(X_{n,r_n}) > \pi_0 + \varepsilon\} \\ &\leq P\{F_n(X_{n,r_n}) > \pi_0 + \varepsilon, X_{n,r_n} \leq x_0 + \eta\} + P\{X_{n,r_n} > x_0 + \eta\} \\ &\leq P\{F_n(x_0 + \eta) > \pi_0 + \varepsilon\} + P\{X_{n,r_n} > x_0 + \eta\}. \end{aligned}$$

Now, by Theorem 1 of Hoeffding [6], we have upon noting that  $F(x_0 + \eta) = \pi_0 + \frac{1}{2}\varepsilon$ ,

$$(3.19) \quad P\{F_n(x_0 + \eta) > \pi_0 + \varepsilon\} \leq \exp(-\frac{1}{2}n\varepsilon^2) = [\rho_1(\varepsilon)]^n,$$

where  $\rho_1(\varepsilon) < 1$ . Also,  $[X_{n,r_n} > x_0 + \eta] \Rightarrow X_{n,r_n}[1 - F(X_{n,r_n})] < \theta - \delta$ , where  $\delta > 0$ . Therefore

$$(3.20) \quad \begin{aligned} P\{X_{n,r_n} > x_0 + \eta\} &\leq P\{X_{n,r_n}[1 - F(X_{n,r_n})] < \theta - \delta\} \\ &\leq P\{X_{n,r_n}[1 - F(X_{n,r_n})] < \theta - \delta, |X_{n,r_n}[F_n(X_{n,r_n}) - F(X_{n,r_n})]| \leq \delta/2\} \\ &\quad + P\{|X_{n,r_n}[F_n(X_{n,r_n}) - F(X_{n,r_n})]| > \delta/2\} \\ &\leq P\{X_{n,r_n}[1 - F_n(X_{n,r_n})] < \theta - \delta/2\} \\ &\quad + P\{|X_{n,r_n}[F_n(X_{n,r_n}) - F(X_{n,r_n})]| > \delta/2\} \\ &\leq P\{Z_n < \theta - \delta/2\} + P\{\sup_x |x[F_n(x) - F(x)]| > \delta/2\}. \end{aligned}$$

Hence, (3.17) follows from (3.18), (3.19), (3.20) and Theorems 2.1 and 3.1.  $\square$

Note that (3.17) implies that

$$(3.21) \quad [\lambda < \infty] \Rightarrow p_n \rightarrow \pi_0 \quad \text{a.s.,} \quad \text{as } n \rightarrow \infty.$$

**4. Proofs of Theorems 1.1 and 1.2.** Since (1.9) implies that  $P\{N(d) < \infty\} = 1$ , we need to prove only (1.9) for Theorem 1.1. Define

$$(4.1) \quad Q_n(d) = P\{N(d) > n\}, \quad n = 0, 1, \dots; Q_0(d) = 1.$$

Then, upon noting that for every  $t > 0$ ,

$$(4.2) \quad E[\exp(tN(d))] \leq 1 + |e^t - 1| \left\{ \sum_{n=1}^{\infty} [\exp(nt)] Q_n(d) \right\},$$

it suffices to show that there exists a positive  $t_0$ , such that

$$(4.3) \quad [\exp(nt_0)]Q_n(d) \rightarrow 0 \quad \text{as } n \rightarrow \infty, \quad \text{for every (fixed) } d > 0.$$

Now, by (1.7) and (1.8),

$$(4.4) \quad \begin{aligned} Q_n(d) &= P\{N(d) > n\} = P\{v_r(d) > r, r = 1, \dots, n\} \\ &\leq P\{v_n(d) > n\} = P\{Z_n^2 > (nd^2/a_n^2)(1/p_n - 1)\} \\ &\leq P\{Z_n^2 > (nd^2/a_n^2)(p_n^{-1} - 1), p_n \leq \pi_0 + \beta\} + P\{p_n > \pi_0 + \beta\}, \end{aligned}$$

where  $\beta > 0$ . Since  $p_n \leq \pi_0 + \beta \Rightarrow p_n^{-1} - 1 \geq \beta^* > \pi_0^{-1} - 1$ , we have

$$(4.5) \quad Q_n \leq P\{Z_n > (n\beta^*)^{1/2}d/a_n\} + P\{p_n > \pi + \beta\}.$$

Now,  $a_n \rightarrow a (> 0)$ , as  $n \rightarrow \infty$ . Hence, for every  $d$ , there exists an  $n_0(d)$  such that for  $n \geq n_0(d)$ ,  $(n\beta^*)^{1/2}d/a_n > \theta + \varepsilon$ , where  $\varepsilon > 0$ . Hence, from (4.5), we have for all  $n \geq n_0(d)$ ,

$$(4.6) \quad Q_n \leq P\{Z_n > \theta + \varepsilon\} + P\{p_n > \pi + \beta\}.$$

Thus, (4.3) directly follows from (4.6), Theorem 3.1 and Theorem 3.4, and the proof of (1.9) is complete.

To prove Theorem 1.2, we note that by (1.7),  $v_n(d) \uparrow \infty$  as  $d \rightarrow 0$ , and hence, by (1.8),  $N(d)$  is non-increasing in  $d (> 0)$ . From (1.7), (3.4) and (3.21), it follows that as  $n \rightarrow \infty$ ,

$$(4.7) \quad Y_n = v_n(d)/\nu(d) \rightarrow 1 \quad \text{a.s.,} \quad \text{uniformly in } d (> 0).$$

Hence,  $\lim_{d \rightarrow 0} v_n(d) = \infty$  a.s., which by (1.8), leads to  $\lim_{d \rightarrow 0} N(d) = \infty$  a.s. Finally, by Theorem 1.1 and the monotone convergence theorem (cf. [7], page 124), it follows that  $\lim_{d \rightarrow 0} EN(d) = \infty$ .

Now, upon writing  $f(n) = na^2/a_n^2$  and  $t = a^2\nu(d)$ , it follows from (4.7) that the conditions of Lemma 1 of Chow and Robbins [3] are all satisfied. Also, by virtue of (3.15) and (3.16), the conditions (C1) and (C2) of Anscombe [1] hold for  $\{Z_n\}$  (these conditions are implicit in [3]). Hence, the proof of (1.10) follows along the lines of Lemma 1 of Chow and Robbins [3] (together with the proofs of their (4) and (5)).

To prove (1.11), we require to show as in Lemma 2 of [3] that  $E(\sup_n Y_n) < \infty$  or verify the conditions of their Lemma 3. Now, by definition,

$$(4.8) \quad Y_n = (a_n^2/a^2)([1 - \pi_0]/\pi_0\theta^2)[Z_n^2 p_n/(1 - p_n)],$$

and hence, it suffices to show that  $E(\sup_n Z_n^2 p_n/(1 - p_n)) < \infty$ . But,

$$(4.9) \quad \begin{aligned} U_n &= Z_n^2 p_n/(1 - p_n) = n^{-2}(n - r_n + 1)r_n X_{n,r_n}^2 \\ &\leq (n^{-1}r_n)(n^{-1} \sum_{i=r_n}^n X_{n,i}^2) \leq n^{-1} \sum_{i=1}^n X_i^2 \quad \text{a.e.,} \end{aligned}$$

and hence, it suffices to show that  $E(\sup_n n^{-1} \sum_{i=1}^n X_i^2) < \infty$ . A sufficient condition for this is, of course, that  $E(X^4) < \infty$ . However, as in Lemma 3 of [3], we prove (1.11) without unnecessarily assuming that  $E(X^4) < \infty$ . For this, consider first the following lemma.

LEMMA 4.1.  $U_n/U_{n-1} \geq (1 - n^{-1})^2$  for all  $n \geq 2$ .

PROOF. Given the sample of size  $n - 1$  i.e.,  $X_{n-1,1} \leq \dots \leq X_{n-1,n-1}$ ,  $X_n$  can belong to one of the  $n$  intervals:  $X_{n-1,i-1} \leq x \leq X_{n-1,i}$ ,  $i = 1, \dots, n$ , where  $X_{n-1,0} = 0$  and  $X_{n-1,n} = \infty$ . If  $X_{n-1,i-1} \leq X_n \leq X_{n-1,i}$ , we have the following two arrays corresponding to the samples of sizes  $n - 1$  and  $n$  respectively:

$$(n - 1)X_{n-1,1}, \dots, (n - i + 1)X_{n-1,i-1}, (n - i)X_{n-1,i}, \dots, X_{n-1,n-1};$$

$$nX_{n-1,1}, \dots, (n - i + 2)X_{n-1,i-1}, (n - i + 1)X_n, (n - i)X_{n-1,i}, \dots, X_{n-1,n-1},$$

where  $(n - r_{n-1})X_{n-1,r_{n-1}}$  and  $(n - r_n + 1)X_{n,r_n}$  are the maximum values within the first and the second rows. Thus, (i) if  $r_{n-1} \geq i$ , we may have either  $r_n = r_{n-1} + 1 > i$ , or  $r_n = r_{n-1} = i$ . In the first case,  $X_{n,r_n} = X_{n-1,r_{n-1}}$  and hence,  $r_n(n - r_n + 1)X_{n,r_n}^2 \geq r_{n-1}(n - r_{n-1})X_{n-1,r_{n-1}}^2$ . In the second case,  $X_{n,r_n} = X_n$ , and hence  $(n - r_n + 1)X_n \geq (n - r_n)X_{n-1,r_n} = (n - r_n)X_{n-1,i}$ . Thus,  $r_n(n - r_n + 1)X_{n,r_n}^2 = r_{n-1}(n - r_{n-1} + 1)X_{n,r_n} \cdot X_{n,r_n} \geq r_n(n - r_{n-1})X_{n-1,r_{n-1}}^2$ . Hence, in either case,

$$(4.10) \quad r_n(n - r_n + 1)X_{n,r_n}^2 \geq r_{n-1}(n - r_{n-1})X_{n-1,r_{n-1}}^2.$$

(ii) If  $r_{n-1} \leq i - 1$ , it is quite evident that  $r_n \geq r_{n-1}$ ,  $X_{n,r_n} \geq X_{n-1,r_{n-1}}$  and  $(n - r_n + 1)X_{n,r_n} \geq (n - r_{n-1})X_{n-1,r_{n-1}}$ . Consequently, (4.12) holds again. Thus,

$$(4.11) \quad \frac{U_n}{U_{n-1}} = \left(\frac{n - 1}{n}\right)^2 \left[\frac{r_n(n - r_n + 1)X_{n,r_n}^2}{r_{n-1}(n - r_{n-1})X_{n-1,r_{n-1}}^2}\right]^2 \geq \left(1 - \frac{1}{n}\right)^2 \quad \text{a.e.}$$

Hence the lemma.

Using now Lemma 4.1, (4.8) and (4.9), the proof of (1.11) follows exactly as in [3, pages 630–631]. Alternatively, a proof similar to the one in (5.10) through (5.14) can be sketched. Hence, the proof of Theorem 1.2 is complete.

**5. Fixed percentage error confidence bands for  $\theta$ .** For every  $d > 0$ , we define  $d_1 = \exp(-d)$  and  $d_2 = \exp(d)$ , so that  $0 < d_1 < 1 < d_2 < \infty$ . We intend to find a confidence interval  $I_n(d) = \{\theta : d_1 Z_n \leq \theta \leq d_2 Z_n\}$  such that

$$(5.1) \quad p\{\theta \in I_n(d)\} = \gamma \quad (0 < \gamma < 1).$$

Our desired sequential confidence interval  $I_{N(d)}(d) = \{Z_{N(d)}d_1 \leq \theta \leq Z_{N(d)}d_2\}$  is based on the stopping (random) variable  $N(d)$ , defined by

$$(5.2) \quad N(d) = \text{smallest integer } n (\geq 1) \text{ for which } p_n \leq nd^2\{nd^2 + a_n^2\}^{-1},$$

where  $p_n$  and  $a_n$  are defined as in Section 1. We also define  $\pi_0$  as in (1.2), and let

$$(5.3) \quad \nu(d) = a^2\pi_0\{(1 - \pi_0)d^2\}^{-1}.$$

**THEOREM 5.1.** *The results of Theorems 1.1 and 1.2 also hold for the sequential procedure in (5.2), with  $\nu(d)$  defined by (5.3).*

PROOF. Note that

$$(5.4) \quad p_n \leq nd^2(nd^2 + a_n^2)^{-1} \Leftrightarrow p_n(1 - p_n)^{-1} \leq nd^2a_n^{-2}.$$

Hence, if we define  $Q_n(d)$  as in (4.1), to prove the results parallel to those in Theorem 1.1, we are only to show that (4.3) holds for the stopping variable  $N(d)$  defined by (5.2). Now, by (5.2) and (5.4),

$$(5.5) \quad Q_n(d) = P\{N(d) > n\} = P\{p_r(1 - p_r)^{-1} > rd^2a_r^{-2}, r = 1, \dots, n\} \\ \leq P\{p_n(1 - p_n)^{-1} > nd^2a_n^{-2}\} = P\{p_n > nd^2(nd^2 + a_n^2)^{-1}\}.$$

Now, for every  $d > 0$ , there exists an  $n_0$ , such that  $nd^2/(nd^2 + a_n^2) \geq \pi_0 + \varepsilon$ , for all  $n \geq n_0$ , where  $\varepsilon > 0$ . Hence, for  $n \geq n_0$ ,

$$(5.6) \quad Q_n(d) \leq P\{p_n > \pi_0 + \varepsilon\},$$

and hence, (4.3) follows directly from Theorem 3.4.

To prove the results parallel to those in Theorem 1.2, we use (3.16) and some standard results on transformation of statistics, and obtain that

$$(5.7) \quad \mathcal{L}(n^{\frac{1}{2}} \log [Z_n/\theta]) \rightarrow \mathcal{N}(0, \pi_0(1 - \pi_0)^{-1}).$$

Also, by (1.1),  $\theta$  is strictly positive, and hence, from (3.4) and Theorem 3.3 it follows that for every positive  $\varepsilon$  and  $\eta$ , there exists a  $\delta > 0$ , such that for all  $n \geq n_0(\varepsilon, \eta)$  and  $N \leq \delta n$ ,

$$(5.8) \quad P\{n^{\frac{1}{2}}|\log Z_{n+j} - \log Z_n| < \varepsilon\{\pi_0/(1 - \pi_0)\}^{\frac{1}{2}}, j = 1, \dots, N\} > 1 - \eta.$$

Hence,  $\{\log Z_n\}$  satisfies both the conditions (C1) and (C2) of Anscombe (1952). We also note that by virtue of (3.21)

$$(5.9) \quad y_n = p_n(1 - \pi_0)/(1 - p_n)\pi_0 \rightarrow 1 \text{ a.s., as } n \rightarrow \infty,$$

and hence, using (5.2), (5.4), (5.7)—(5.9) and Lemma 1 of [3], it follows that (1.9) holds for the stopping rule (5.2). To prove (1.11), we proceed as follows.

Choose some arbitrarily small  $\varepsilon (> 0)$ , and defining  $\nu(d)$  as in (5.3), let

$$(5.10) \quad n_1(d) = [\nu(d)(1 - \varepsilon)] \quad \text{and} \quad n_2(d) = [\nu(d)(1 + \varepsilon) + 1].$$

Then,

$$(5.11) \quad E\{N(d)/\nu(d)\} = [\nu(d)]^{-1}[\sum_1 + \sum_2 + \sum_3 nP\{N(d) = n\}],$$

where the summation  $\sum_1$  extends over  $n \leq n_1(d)$ ,  $\sum_2$  over  $n_1(d) < n \leq n_2(d)$  and  $\sum_3$  over  $n > n_2(d)$ . Since  $\lim_{d \rightarrow 0} \nu(d) = \infty$  and  $N(d)/\nu(d) \rightarrow 1$  a.s., as  $d \rightarrow 0$ , for every  $\varepsilon > 0$ , we can find a  $d_0 (> 0)$ , such that for  $0 < d \leq d_0$ ,  $P\{n_1(d) < N(d) \leq n_2(d)\} = P\{1 - \varepsilon \leq N(d)/\nu(d) \leq 1 + \varepsilon\} > 1 - \eta$ , where  $\eta (> 0)$  is a preassigned small number. Then, for  $d \leq d_0$ , the first sum on the right-hand side of (5.11) is less than

$$(5.12) \quad (1 - \varepsilon)P\{N(d) < n_1(d)\} \leq \eta(1 - \varepsilon) \leq \eta.$$

The second sum is equal to  $1 + R(d)$ , where

$$(5.13) \quad |R(d)| \leq \varepsilon P\{n_1(d) < N(d) \leq n_2(d)\} \\ + [1 - P\{n_1(d) < N(d) \leq n_2(d)\}] \leq \varepsilon + \eta.$$

Finally, on using (5.5), we have on noting that  $Q_{n_2(d)}(d) = P\{N(d)/\nu(d) \geq 1 + \varepsilon\}$  that

$$\begin{aligned}
 & [\nu(d)]^{-1} \sum_3 nP\{N(d) = n\} \\
 &= [\nu(d)]^{-1} \{ \sum_{n_2(d)+1}^{\infty} Q_n(d) + [n_2(d) + 1]Q_{n_2(d)}(d) \} \\
 &\leq [\nu(d)]^{-1} [ \sum_{n_2(d)}^{\infty} P\{p_n > nd^2/(nd^2 + a_n^2)\} ] \\
 (5.14) \quad &+ \{ [n_2(d) + 1]/\nu(d) \} Q_{n_2(d)}(d) \\
 &\leq [\nu(d)]^{-1} \sum_{n_2(d)}^{\infty} P\{p_n > \pi_0(1 + \varepsilon)[(1 + \varepsilon)\pi_0 + (1 - \pi_0)a_n^2/a^2]^{-1}\} \\
 &+ \{ [n_2(d) + 1]/\nu(d) \} \eta \\
 &\leq [\nu(d)]^{-1} \sum_{n_2(d)}^{\infty} P\{p_n > \pi_0 + \varepsilon'\} + \{ \eta [n_2(d) + 1]/\nu(d) \}; \quad \varepsilon' > 0.
 \end{aligned}$$

Hence, by Theorem 3.4 and (5.10), it follows that the right-hand side of (5.14) can be made arbitrarily small by letting  $d$  be small. Hence, (1.11) follows from (5.11) through (5.14).  $\square$

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