

## SAMPLE SIZE SAVINGS FOR CURTAILED ONE-SAMPLE NONPARAMETRIC TESTS FOR LOCATION SHIFT

BY NIRA HERRMANN<sup>1</sup> AND TED H. SZATROWSKI<sup>2</sup>

*Drexel University and Rutgers University*

Asymptotic moments of normed sample size savings are derived for one-sided curtailed nonparametric tests for symmetry for testing location shift hypotheses under the null hypothesis and contiguous alternatives. The contiguous alternative results are derived using Feller's (1943) central limit theorem result for large deviations and techniques used in Albers, Bickel and van Zwet (1976).

**1. Introduction.** The first step from the traditional fixed sample size test towards sequential or random sample size tests is curtailed sampling. In the curtailed procedures under consideration in this paper, sampling is stopped as soon as it is clear that the decision for the fixed sample size test has become irrevocable. Thus curtailed sampling gives us a testing procedure with the same power function as that of the fixed sample size test, while guaranteeing that the random sample size is less than or equal to the fixed sample size in all cases.

Curtailed binomial or sign tests have been frequently investigated in the area of quality control. Alling (1966), Phatak and Bhatt (1967), Craig (1968), Cohen (1970), and Shah and Phatak (1972, 1974) all do calculations of average sample size when curtailed sampling is used. Garner (1958) discussed curtailed sampling when a continuous variable is used for testing lot acceptance. Anderson and Friedman (1960) and Samuel (1970) compare the expected savings using curtailed sampling procedures versus sequential probability ratio tests. Herrmann and Szatrowski (1982, 1985) derive and evaluate the small sample properties of asymptotic formulas for the expected sample size savings for curtailed binomial tests. Eisenberg and Ghosh (1980, 1981) derive expressions for the asymptotic efficiency of curtailed tests under fixed and contiguous alternative hypotheses. The curtailed version of the  $t$ -test and Hotelling's  $T^2$  have been described by Brown, Cohen and Strawderman (1979) and savings in sample size were investigated by Herrmann and Szatrowski (1980). Wong and Wong (1982) define and examine the behavior of a curtailed procedure for the location parameter of the Weibull distribution.

Halperin and Ware (1974), Verter (1979) and DeMets and Halperin (1982) study curtailed sampling for a two-sample problem with applications to clinical

---

Received February 1984; revised May 1986.

<sup>1</sup>Research supported by the National Institute of Environmental Health Sciences Young Investigator Award No. 1-R23-ES-02131.

<sup>2</sup>Research supported by Rutgers University Graduate School of Management Summer 1982, 1983 and 1985 Research Fellowships.

AMS 1980 *subject classifications*. Primary 62G10; secondary 62E20.

*Key words and phrases*. Asymptotic distributions, clinical trials, contiguous alternatives, curtailed sampling, distribution free tests, large deviations, linear rank tests, van der Waerden scores, Wilcoxon test.

trials. The Halperin and Ware (1974) asymptotic result is of a different order than the result obtained here due to their assumption that the sequential observations were obtained in nondecreasing order. Pocock (1977) and O'Brien and Fleming (1979) investigate group sequential approaches to clinical trials. Lan, Simon and Halperin (1982) report on results for stochastically curtailed tests, and Pasternack (1984) discusses curtailed tests involving the probability of a reversal of a decision based on incomplete sequential data. DeMets and Lan (1984) review many of these applications to sequential trials.

In this paper, we characterize the random savings in sample size. We begin with a formal description of the problem.

**2. The problem.** Let  $X_1, \dots, X_n$  be an independent, identically distributed sequence of random variables, observed sequentially, from a continuous distribution function with density  $f(x - \theta)$ , where  $f(x)$  is symmetric about zero and  $\theta$  is the location shift parameter. Let  $a_{i,n}$ ,  $i = 1, \dots, n$ , be a set of nonnegative and nondecreasing scores in  $i$ ,  $a_{1,n} \leq \dots \leq a_{n,n}$ . Let  $Z_i = |X_i|$  and let  $Z_{(i)}$  be the  $i$ th order statistic formed from  $Z_1, \dots, Z_n$ . The usual nonparametric statistic for location based on this sample of size  $n$  is given by  $S_n = \sum_1^n a_{i,n} W_i$ , where  $W_i = 1$  if the observed  $X$  value corresponding to  $Z_{(i)}$  is positive;  $W_i = 0$  otherwise. We assume (e.g., Hájek and Šidák (1967), Puri and Sen (1971)) that the scores  $a_{i,n}$  can be imbedded in a nondecreasing score function  $J: [0, 1) \rightarrow [0, \infty)$ , where  $J$  is square integrable,  $\int_0^1 J(t) dt > 0$ , and  $\lim_{n \rightarrow \infty} a_{[un]+1, n} = J(u)$ ,  $0 \leq u < 1$  ( $[\cdot]$  is the greatest integer function). Also  $\int_0^1 (a_{[un]+1, n} - J(u))^2 du = o(1)$  and both  $|J(u)| \leq K(1 - u)^{\delta-1/2}$  and  $|dJ(u)/du| \leq K(1 - u)^{\delta-3/2}$  for some  $K$  and  $0 < \delta \leq \frac{1}{2}$ . Often,  $a_{i,n} = J(i/(n + 1))$ .

For the one-sided hypothesis test for location shift, testing  $H_0: \theta = 0$  versus  $H_A: \theta > 0$  with significance level  $\alpha$ , we reject the null hypothesis if  $S_n \geq k_n(\alpha)$ ; otherwise, we accept the null hypothesis. We will assume that the significance level  $\alpha$  has been chosen so that there exists a  $k_n(\alpha)$  with the property that  $\alpha = \Pr\{S_n \geq k_n(\alpha) | \theta = 0\}$  so as to avoid randomized tests, since results for randomized tests can easily be obtained from our nonrandomized test results. It is well known (e.g., Hájek and Šidák (1967), Chapter 5) that the statistic  $S_n$  is asymptotically normally distributed with mean  $\sum a_{i,n}/2$  and variance  $\sum (a_{i,n})^2/4 \sim n \int_0^1 J^2(t) dt/4$  under the null hypothesis of symmetry. Thus, for large  $n$ , we can use this result to find an approximate value for  $k_n(\alpha)$  given by

$$\begin{aligned}
 (2.1) \quad 2k_n(\alpha) &\approx 2\{E(S_n | \theta = 0) + z_{1-\alpha}\{\text{Var}(S_n | \theta = 0)\}^{1/2}\} \\
 &= \sum a_{i,n} + z_{1-\alpha}\left(\sum \{a_{i,n}\}^2\right)^{1/2},
 \end{aligned}$$

where  $z_{1-\alpha}$  is the upper  $(1 - \alpha)$ th percentile of the standard normal distribution.

A curtailed version of this test can be constructed with the identical power function and a random sample size less than or equal to the fixed sample size  $n$ . We define  $S_{m,n} = \sum_1^m a_{i,n} W_{i,m}$ , where  $W_{i,m}$  are the  $W_i$  scores based on the order statistics of the absolute values of  $X_i$ ,  $i = 1, \dots, m$ . Thus,  $S_{m,n}$  is a test statistic

with the  $W$ 's based on the first  $m$  observations but using the scores for a sample of size  $n$ . Note that for any outcome,  $S_{m,n}$  is nondecreasing in  $m$ .

The one-sided curtailed test procedure for testing  $H_0: \theta = 0$  versus  $H_A: \theta > 0$  stops at the earliest stage  $m$  of the experiment when either  $S_{m,n} \geq k_n(\alpha)$  (reject the null hypothesis) or  $S_{m,n} + \sum_{m+1}^n a_{i,n} < k_n(\alpha)$  (accept the null hypothesis). If neither condition occurs at stage  $m$ , sampling is continued. Note that this procedure terminates on or before  $n$  observations have been collected. Let  $N^R$  be the random stopping time when the curtailed procedure is used and we reject the null hypothesis, with  $N^R \equiv n$  if we accept the null hypothesis. Let  $N^A$  be the random stopping time when the curtailed procedure is used and we accept the null hypothesis with  $N^A \equiv n$  if we reject the null hypothesis. We note that at least one of  $N^R$  or  $N^A$  (and possibly both) are equal to  $n$  for each experiment and that  $N^R$  and  $N^A$  are defined for every outcome.

Our focus in this paper will be on characterizing the asymptotic distributions of normed versions of the sample size savings  $(n - N^R)$  and  $(n - N^A)$ . We will investigate results for the one-sided hypothesis with  $H_A: \theta > 0$  since we can transform the one-sided hypothesis testing problem with  $H_A: \theta < 0$  into a one-sided hypothesis test with  $H_A: \theta > 0$  by using  $-X_1, \dots, -X_n$  as the observed sample. Because of the definition of  $N^R$  and  $N^A$ , the  $r$ th moment of the total sample size savings can be expressed as  $E\{(n - N^R)^r|\theta\} + E\{(n - N^A)^r|\theta\}$ , for  $r = 1, 2, \dots$ , without weighting.

**3. Savings under contiguous alternatives.** In this section results are presented that characterize the distribution of normed versions of the random variables  $n - N^R$  and  $n - N^A$  under values of  $\theta$  that are close to the null value ( $\theta$  is characterized in (3.1) and (3.2)). The moments of normed versions of these random savings are given in Theorems 3.1 and 3.2. In Section 4, we define the specific norming constants and limit constants in (3.3) and (3.4) for bounded score functions  $J$  and for several unbounded score functions, including the van der Waerden scores. Using these results, we show in Section 5 that the normed sample size savings have an asymptotic truncated normal distribution for many of the nonparametric tests under consideration, including the Wilcoxon and the van der Waerden tests. A brief sketch of the proofs for these results is given in this section with details deferred to the Appendix.

Let  $\{\theta_i\}$  be a sequence of parameter values converging to zero with the properties

$$(3.1) \quad \theta_i = O(n^{-1/2}),$$

$$(3.2) \quad 1 - \beta_n = \Pr\{S_n \geq k_n(\alpha)|\theta_n\} \rightarrow 1 - \beta, \quad 0 < \beta < 1.$$

Define

$$(3.3) \quad b_{m,n} = \{k_n(\alpha) - E(S_{n-m,n}|\theta_n)\}/(\text{Var}(S_{n-m,n}|\theta_n))^{1/2},$$

$$(3.4) \quad c_{m,n} = b_{m,n} - \left\{ \left( \sum_{n-m+1}^n a_{i,n} \right) / (\text{Var}(S_{n-m,n}|\theta_n))^{1/2} \right\}.$$

We will assume that there exists a norming sequence  $h(n) \rightarrow \infty$ ,  $h(n) = O(n^{1/2})$  or  $o(n^{1/2})$ , with the property that, for  $\frac{1}{2} < \eta \leq 1$ , and  $b$  and  $c$  positive,

$$(3.5) \quad \lim_{n \rightarrow \infty} (z_{1-\beta} + b_{[t_n h(n)], n}) / t_n^\eta = b,$$

$$(3.6) \quad \begin{aligned} \lim_{n \rightarrow \infty} (bt_n^\eta - b_{[t_n h(n)], n}) &= z_{1-\beta}; \\ \lim_{n \rightarrow \infty} (z_{1-\beta} + c_{[t_n h(n)], n}) / t_n^\eta &= -c, \\ \lim_{n \rightarrow \infty} (ct_n^\eta + c_{[t_n h(n)], n}) &= -z_{1-\beta}, \end{aligned}$$

where this convergence is uniform for all sequences  $\{t_n\}$  satisfying  $h^{-1}(n) < t_n < Kn^\epsilon$  for some constant  $K$  and  $0 < \epsilon < \frac{1}{2}$  with  $\liminf t_n > 0$ .

It may be helpful to think of  $h(n) = n^{1/2}$ ,  $\eta = 1$  and  $r = 1$  in a first reading of Theorems 3.1 and 3.2, where we characterize the asymptotic moments of  $(n - N^R)/h(n)$  and  $(n - N^A)/h(n)$ . Note that with these values,  $E\{((n - N^R)/h(n))^r | \theta_n\}$  becomes  $n^{1/2} E\{((n - N^R)/n)^r | \theta_n\}$ , which is a normed version of the average fraction sample size savings achieved by stopping early and rejecting the null hypothesis.

**THEOREM 3.1.** *For the curtailed one-sided hypothesis test described in Section 2, assuming (3.1), (3.2) and (3.5), for  $r$  a positive integer,*

$$(3.7) \quad \lim_{n \rightarrow \infty} E\{((n - N^R)/h(n))^r | \theta_n\} = \int_0^\infty r t^{r-1} \Phi(z_{1-\beta} - bt^\eta) dt.$$

**PROOF.** A brief outline of the proof is given here. Details are deferred to the Appendix. Let  $n^R$  be the smallest sample size at which the curtailed test could stop and reject the null hypothesis, i.e., the integer value of  $m$  satisfying

$$(3.8) \quad \sum_1^{m-1} a_{i,n} < k_n(\alpha) \leq \sum_1^m a_{i,n}.$$

Then  $E\{((n - n^R)/h(n))^r | \theta_n\}$  becomes

$$(3.9) \quad h^{-r}(n) \sum_{m=n^R}^{n-1} (n - m)^r \Pr\{N^R = m | \theta_n\}.$$

We can convert these sums into sums of cumulative probabilities to yield an expression asymptotically equal to (3.9):

$$(3.10) \quad h^{-r}(n) \sum_{m=1}^{n-n^R} r m^{r-1} \Pr\{N^R \leq n - m | \theta_n\}.$$

We note that the ratio of (3.9) and (3.10) converges to one unless (3.9) goes to zero, in which case (3.10) also goes to zero. Observe that we are summing from the largest to the smallest probabilities. The substitution  $\{N^R \leq n - m\} = \{S_{n-m,n} \geq k_n(\alpha)\}$  into (3.10) yields

$$(3.11) \quad h^{-r}(n) \sum_{m=1}^{n-n^R} r m^{r-1} \Pr\{S_{n-m,n} \geq k_n(\alpha) | \theta_n\}.$$

We then normalize  $S_{n-m, n}$  to obtain

$$(3.12) \quad E\{((n - N^R)/h(n))^r | \theta_n\} = h^{-r}(n) \sum_{m=1}^{n-n^R} rm^{r-1} \Pr\{S_{n-m, n}^* \geq b_{m, n} | \theta_n\},$$

where

$$S_{n-m, n}^* = \{S_{n-m, n} - E(S_{n-m, n} | \theta_n)\} / (\text{Var}(S_{n-m, n} | \theta_n))^{1/2}$$

and  $b_{m, n}$  is given in (3.3).

Since  $b_{n-n^R, n} \rightarrow \infty$ , we need a large deviation central limit theorem for signed rank tests under contiguous alternatives to proceed further. The needed result is obtained using a central limit theorem of Feller (1943) and the techniques of Albers, Bickel and van Zwet (1976). (See Appendix A.) This large deviation result is applied to the first  $m_n$  (largest) terms of the sum, where  $m_n$  is chosen so that  $m_n/h(n) \rightarrow \infty$ , and the remaining terms are negligible. We then obtain

$$(3.13) \quad h^{-r}(n) \sum_{m=1}^{m_n} rm^{r-1} \Phi(-b_{m, n}),$$

which has the property that the absolute difference between (3.12) and (3.13) is  $o(1)$ . (See Appendix A.) Furthermore, this sum differs from the integral (3.14) by  $o(1)$ :

$$(3.14) \quad h^{-r}(n) \int_1^{m_n} rm^{r-1} \Phi(-b_{m, n}) dm,$$

where we use asymptotic expansions (e.g., Lemmas 4.1 and 4.2) to define  $b_{m, n}$  for noninteger values of  $m$ . (See Appendix B.) We then make the change of variable  $m = h(n)t$  to obtain

$$(3.15) \quad \int_0^\infty rt^{r-1} \Phi(-b_{[h(n)t], n}) I(h^{-1}(n) \leq t \leq (m_n/h(n))) dt,$$

where  $I(\cdot)$  is the indicator function. Taking the limit as  $n \rightarrow \infty$ , using the dominated convergence theorem to take the limit under the integral sign and using assumption (3.5) yields the desired result. (See Appendix C.)  $\square$

**THEOREM 3.2.** *For the curtailed one-sided hypothesis test described in Section 2, assuming (3.1), (3.2), (3.5) and (3.6), for  $r$  a positive integer,*

$$(3.16) \quad \lim_{n \rightarrow \infty} E\{((n - n^A)/h(n))^r | \theta_n\} = \int_0^\infty rt^{r-1} \Phi(-z_{1-\beta} - ct^n) dt.$$

**PROOF.** A brief outline of the proof is given here. The details are very similar to the proof of Theorem 3.1 and are thus omitted. Let  $n^A$  be the smallest sample size for which the curtailed test could stop and accept the null hypothesis, i.e., the integer value of  $m$  satisfying

$$\sum_{i=m+1}^n a_{i, n} < k_n(\alpha) \leq \sum_{i=m}^n a_{i, n}.$$

Then  $E\{((n - N^A)/h(n))^r|\theta_n\}$  becomes

$$(3.17) \quad h^{-r}(n) \sum_{m=n^A}^{n-1} (n - m)^r \Pr\{N^A = m|\theta_n\}.$$

The remaining details of the proof are similar to those of the proof of Theorem 3.1 using the substitution  $\{N^A \leq m\} = \{S_{m,n} + \sum_{m+1}^n \alpha_{i,n} < k_n(\alpha)\}$  and with “ $-b$ ” replaced by “ $c$ ” in (3.13)–(3.15).  $\square$

**4. Evaluation of  $h(n)$  and the constants in (3.5) and (3.6).**

**THEOREM 4.1.** *For bounded score functions, i.e.,  $J(1 - ) \equiv \lim_{u \uparrow 1} J(u) < \infty$ , (3.5) and (3.6) are satisfied when  $h(n) = n^{1/2}$ ,  $\eta = 1$ , and  $b$  and  $c$  are given by*

$$(4.1) \quad b = c = J(1 - ) \left( \int_0^1 J^2(u) du \right)^{-1/2}.$$

Before proving Theorem 4.1, we state two lemmas that give us the asymptotic mean and variance of  $S_n$  and  $S_{n-m,n}$  under contiguous alternatives. A well-known result (e.g., Hájek and Šidák (1967), Chapter 6) when  $f$  is the symmetric density function from Section 2 is given in:

**LEMMA 4.1.** *Under conditions (3.1) and (3.2),  $S_n$  is asymptotically normally distributed with*

$$(4.2) \quad 2E(S_n|\theta_n) \approx n \int_0^1 J(u) du + n\theta_n \int_0^1 J(u) J^*(u, f) du,$$

$$(4.3) \quad 4 \text{Var}(S_n|\theta_n) \approx n \int_0^1 J^2(u) du,$$

where

$$J^*(u, f) = f'(F^{-1}((u + 1)/2)) / f(F^{-1}((u + 1)/2)), \quad 0 < u < 1,$$

and  $F$  is the cumulative distribution function of  $f$ , assuming  $f'(x)$  exists for  $x > 0$ .

**LEMMA 4.2.** *Under conditions (3.1) and (3.2),  $S_{[n(1-s)],n}$ ,  $0 < s < 1$ , is asymptotically normally distributed with mean and variance given by*

$$(4.4) \quad \begin{aligned} 2E(S_{[n(1-s)],n}|\theta_n) &\approx n(1 - s) \int_0^1 J((1 - s)u) du \\ &\quad + n(1 - s)\theta_n \int_0^1 J((1 - s)u) J^*(u, f) du \\ &\equiv 2\mu_n(s, \theta_n), \end{aligned}$$

$$(4.5) \quad 4 \text{Var}(S_{[n(1-s)],n}|\theta_n) \approx n(1 - s) \int_0^1 J^2((1 - s)u) du \equiv 4\sigma_n^2(s, \theta_n).$$

**PROOF.** Lemma 4.2 follows from the results of Lemma 4.1 by noting that  $S_{[n(1-s)],n}$  is based on a sample size of  $[n(1-s)]$  and that only the first  $[n(1-s)]$  of the  $n$  scores are used.  $\square$

The proof of Theorem 4.1 will provide us with insight into how to choose  $h(n)$  for unbounded score functions and how to achieve better small sample estimates using  $b_n$  and  $c_n$  rather than  $b$  or  $c$ .

**PROOF OF THEOREM 4.1.** Using the asymptotic normality of  $S_n$  and (3.2), we find

$$(4.6) \quad k_n(\alpha) \approx E(S_n|\theta_n) - z_{1-\beta_n}(\text{Var}(S_n|\theta_n))^{1/2},$$

which, when substituted into (3.3), yields

$$(4.7) \quad -b_{m,n} \approx z_{1-\beta_n} [\text{Var}(S_n|\theta_n)/\text{Var}(S_{n-m,n}|\theta_n)]^{1/2} - [E(S_n|\theta_n) - E(S_{n-m,n}|\theta_n)]/[\text{Var}(S_{n-m,n}|\theta_n)]^{1/2}.$$

The proof is in three parts. First, we show that the first term on the right-hand side (RHS) of (4.7) converges to  $z_{1-\beta}$ . Then we show that the second term behaves asymptotically like  $bt_n$ . Finally, to establish the form of the constant  $c$ , we show the second term on the RHS of (3.4) behaves asymptotically like  $-2bt_n$ .

Using the asymptotic variance from (4.5), we see that the ratio of the variances in the first term of the RHS of (4.7) becomes

$$(4.8) \quad \int_0^1 J^2(u) du / \left\{ (1 - t_n h(n)/n) \int_0^1 J^2((1 - t_n h(n)/n)u) du \right\},$$

which converges to one since  $t_n h(n) = o(n)$ .

We next focus on the second term, first considering the normed numerator

$$(4.9) \quad n^{-1/2} [E(S_n|\theta_n) - E(S_{n(1-t_n h(n)/n),n}|\theta_n)],$$

with the  $n^{-1/2}$  factor arising from the denominator, which is  $O(n^{1/2})$ . To satisfy (3.5), we must find an  $h(n)$  so that (4.9) divided by  $t_n^n$  converges to a constant, say  $b^*$ . We can rewrite (4.9) using (4.4) to obtain

$$(4.10) \quad n^{-1/2} [\mu_n(0, \theta_n) - \mu_n(t_n h(n)/n, \theta_n)],$$

in the notation of Lemma 4.2. For bounded score functions, we can expand  $\mu_n(s, \theta_n)$  for small  $s$  in a Taylor series yielding

$$(4.11) \quad \mu_n(s, \theta_n) \approx \mu_n(0, \theta_n) + (\partial \mu_n(s, \theta_n)/\partial s)|_{s=0} s.$$

Using this result, (4.10) becomes asymptotically equal to

$$(4.12) \quad -n^{-1/2} (\partial \mu_n(s, \theta_n)/\partial s)|_{s=0} (t_n h(n)/n).$$

Since  $\mu_n = O(n)$ , we choose  $h(n) = n^{1/2}$  and find the limit as  $n \rightarrow \infty$  of (4.12)

without the factor  $t_n$  to be

$$(4.13) \quad - \lim_{n \rightarrow \infty} n^{-1}(\partial\mu_n(s, \theta_n)/\partial s)|_{s=0} = -n^{-1}(\partial\mu_n(s, 0)/\partial s)|_{s=0},$$

since  $\theta_n \rightarrow 0$ . Using (4.4), the RHS of (4.13) becomes

$$(4.14) \quad \left( \int_0^1 J(u) du + \int_0^1 uJ'(u) du \right) / 2,$$

which, by using integration by parts, can be shown to equal  $J(1 - )/2$ .

The denominator of the second term in (4.7) converges to  $(\int_0^1 J^2(u) du)^{1/2}/2$  using (4.5), the substitutions  $m = h(n)t_n$  and

$$\begin{aligned} 4n^{-1}\text{Var}(S_{[n(1-th(n)/n)], n}|\theta_n) &\simeq (1 - th(n)/n) \int_0^1 J^2((1 - th(n)/n)u) du \\ &\rightarrow \int_0^1 J^2(u) du, \end{aligned}$$

and recalling that a factor of  $n^{-1/2}$  was taken from the denominator in the evaluation of the numerator.

To evaluate (3.6), we note that with  $m = [sn]$ ,

$$(4.15) \quad \sum_{[n(1-s)]+1}^n a_{i,n} \sim n \int_{1-s}^1 J(u) du = 2(\mu_n(0, 0) - \mu_n(s, 0)).$$

Replacing  $s$  with  $t_n h(n)/n$  and using the Taylor series expansion in (4.11) with  $\theta_n = 0$  yields

$$(4.16) \quad \begin{aligned} n^{-1/2} \sum_{[n(1-t_n h(n)/n)]+1}^n a_{i,n} &\sim -2(\partial\mu_n(s, 0)/\partial s)|_{s=0} (t_n h(n)/n^{3/2}) \\ &\sim 2(J(1 - )/2)t_n. \end{aligned}$$

The desired result is obtained by combining (4.16) with the asymptotic results obtained for  $b_{[th(n)], n}$  into (3.4) and then into (3.6). Note that with  $m = h(n)t_n$  and for values of  $m$  for which  $h^{-1}(n) < t_n < Kn^\epsilon$  for some positive  $K$  and  $0 < \epsilon < \frac{1}{2}$  as in (3.5) and (3.6), we have  $m/n \leq Kn^{\epsilon+1/2}/n = o(1)$  in the above, so that Lemma 4.2 is valid for large  $n$  when  $s$  satisfies  $0 < Kn^{\epsilon-1/2} < s < 1$ . □

To apply the asymptotic results to small samples, it is useful to note the form of the terms in (3.5) and (3.6) for large  $n$ . For a specific sample size of  $n$ , we prefer to use  $1 - \beta_n$  rather than  $1 - \beta$ . In addition, we can improve the small sample approximation by deriving, from the proof of Theorem 4.1, values for  $b_n$  and  $c_n$  that satisfy  $b_n \sim b$  and  $c_n \sim c$  for both bounded and unbounded score functions and which we will use in place of  $b$  and  $c$ . Further simplifications are possible for bounded score functions. These results are noted in Lemma 4.3. We can also deduce from the proof a sufficient condition for calculating  $h(n)$  for unbounded score functions. This result is given in Lemma 4.4.

**LEMMA 4.3.** *For small sample size  $n$  applications of Theorem 3.1 and Theorem 3.2, use of  $b_n$  and  $c_n$  instead of  $b$  and  $c$ , respectively, may improve the*



approximations, where

$$(4.17) \quad b_n = t^{-\eta} \{ E(S_n | \theta_n) - E(S_{[n(1-th(n)/n)]} | \theta_n) \} \\ \times \{ \text{Var}(S_{[n(1-th(n)/n)]} | \theta_n) \}^{-1/2},$$

$$(4.18) \quad c_n = -b_n + t^{-\eta} \left\{ \sum_{[th(n)]+1}^n \alpha_{i,n} \right\} \{ \text{Var}(S_{[n(1-th(n)/n)]} | \theta_n) \}^{-1/2},$$

and it is expected that  $b_n$  and  $c_n$  do not depend upon  $t > 0$ . If  $J(1 - ) < \infty$  with  $h(n) = n^{1/2}$  and  $\eta = 1$ , then  $b_n$  and  $c_n$  as previously given simplify to

$$(4.19) \quad b_n = -n^{-1/2} (\partial \mu_n(s, \theta_n) / \partial s)|_{s=0} / \sigma_n(0, \theta_n),$$

$$(4.20) \quad c_n = -n^{-1/2} \{ 2(\partial \mu_n(s, 0) / \partial s)|_{s=0} - (\partial \mu_n(s, \theta_n) / \partial s)|_{s=0} \} / \sigma_n(0, \theta_n),$$

where  $\mu_n$  and  $\sigma_n$  are defined in Lemma 4.2.

PROOF. (4.17) and (4.18) follow after noting the form of the limit in (3.5), (3.6) and (4.7). (4.19) and (4.20) follow similarly using (4.13) and (4.16) also.  $\square$

LEMMA 4.4. For contiguous alternatives, it is sufficient for (3.5) and (3.6) to choose  $h(n)$  and  $\eta$  so that

$$(4.21) \quad n^{1/2} \int_{1-th(n)/n}^1 J(u) du \sim b^* t^\eta, \quad b^* > 0, \frac{1}{2} < \eta \leq 1.$$

PROOF. We note the form of (4.10) in the proof of Theorem 4.1 and that  $\theta_n \rightarrow 0$  so that the limit needs to be evaluated for the term

$$(4.22) \quad n^{-1/2} (\mu_n(0, 0) - \mu_n(th(n)/n, 0)),$$

which, using (4.4), yields (4.21).  $\square$

We conclude this section with the results of straightforward applications of Lemma 4.4 to two examples of unbounded score functions.

LEMMA 4.5. Let  $h(n) = (n/\log n)^{1/2}$ . Then, for the van der Waerden score function  $J(u) = \Phi^{-1}((u+1)/2)$ ,  $0 < u < 1$ , evaluation of (4.21) yields  $\eta = 1$  and  $b^* = 1$ .

LEMMA 4.6. Let  $h(n) = n^{2\delta/(2\delta+1)}$ . Then, for the family of score functions  $J(u) = (1-u)^{\delta-1/2}$ ,  $0 < \delta < \frac{1}{2}$ ,  $0 < u < 1$ , evaluation of (4.21) yields  $\eta = \delta + \frac{1}{2}$  and  $b^* = 2/(2\delta+1)$ .

**5. Asymptotic convergence to truncated normal when  $\eta = 1$ .** When  $\eta = 1$ , it is easy to show that  $(n - N^R)/h(n)$  and  $(n - N^A)/h(n)$  converge to truncated normal distributions using Theorems 3.1 and 3.2 once we have established some properties of the truncated normal distribution.

**DEFINITION.** Let  $N^*(\mu, \sigma^2, c)$  be a random variable from a normal distribution, with mean  $\mu$  and variance  $\sigma^2$ , which has been truncated from above at  $c$ , the mass above  $c$  being placed at  $c$ . Let  $N_*(\mu, \sigma^2, c)$  be similarly defined as truncated below at  $c$ .

Note that if we know  $\mu, c$  and the percentile at which  $c$  occurs, we know  $\sigma^2$  and have completely specified the truncated normal distribution. It is easy to verify the following relationships involving linear transformations of truncated normal distributions.

**LEMMA 5.1.**

$$aN^*(\mu, \sigma^2, c) + b = \begin{cases} N^*(a\mu + b, a^2\sigma^2, ac + b) & \text{for } a > 0, \\ N_*(a\mu + b, a^2\sigma^2, ac + b) & \text{for } a < 0; \end{cases}$$

$$aN_*(\mu, \sigma^2, c) + b = \begin{cases} N_*(a\mu + b, a^2\sigma^2, ac + b) & \text{for } a > 0, \\ N^*(a\mu + b, a^2\sigma^2, ac + b) & \text{for } a < 0. \end{cases}$$

Let  $L(X)$  denote the distribution function of the random variable  $X$ .

**THEOREM 5.1.** Under the assumptions of Theorems 3.1 and 3.2, when  $\eta = 1$ ,

$$(5.1) \quad \lim_{n \rightarrow \infty} L((n - N^R)/h(n)) = L(N_*(b^{-1}z_{1-\beta}, b^{-2}, 0)),$$

$$(5.2) \quad \lim_{n \rightarrow \infty} L((n - N^A)/h(n)) = L(N_*(-c^{-1}z_{1-\beta}, c^{-2}, 0)).$$

**PROOF.** If we make the change of variables  $u = z_{1-\beta} - bt$ , (3.7) becomes

$$(5.3) \quad \lim_{n \rightarrow \infty} E\{((n - N^R)/h(n))^r | \theta_n\} = b^{-r} \int_{-\infty}^{z_{1-\beta}} r(z_{1-\beta} - u)^{r-1} \Phi(u) du.$$

From (5.1) and Lemma 5.1, we see that the limit of the  $r$ th moment is of the form

$$(5.4) \quad E\{b^{-1}(z_{1-\beta} - N^*(0, 1, z_{1-\beta}))^r\} = E\{N_*(b^{-1}z_{1-\beta}, b^{-2}, 0)^r\},$$

thus establishing (5.1). (5.2) follows similarly.  $\square$

### APPENDIX A

**Justification of (3.13) using large deviation results.** To justify going from (3.12) to (3.13), we show that (3.12) minus (3.13) is  $o(1)$ , i.e.,

$$h^{-r}(n) \sum_{m=1}^{n-n^R} rm^{r-1} (\Pr\{S_{n-m, n}^* \geq b_{m, n}\} - \Phi(-b_{m, n})) = o(1).$$

We do this by showing (A.1) in Section A.2 and (A.2) in Section A.3:

$$(A.1) \quad h^{-r}(n) \sum_{m=1}^{n-n^R} rm^{r-1} \left[ \Pr\{(S_{n-m,n} - E(S_{n-m,n}|Z)) \geq b_{m,n}(\text{Var}(S_{n-m,n}|Z))^{1/2}\} - \Phi(-b_{m,n}) \right] = o(1);$$

$$(A.2) \quad h^{-r}(n) \sum_{m=1}^{n-n^R} rm^{r-1} \left[ \Pr\{S_{n-m,n}^* \geq b_{m,n}\} - \Pr\{S_{n-m,n} - E(S_{n-m,n}|Z) \geq b_{m,n}(\text{Var}(S_{n-m,n}|Z))^{1/2}\} \right] = o(1).$$

We divide  $\sum_1^{n-n^R}$  into  $\sum_1^{m_n} + \sum_{m_n+1}^{n-n^R}$  and choose  $m_n$  so that  $b_{m_n,n} = \gamma_n \rightarrow \infty$  at a rate slow enough that we can apply a large deviation central limit theorem result to the  $m \leq m_n$  terms, and fast enough that the second sum is easily shown to be  $o(1)$ . The large deviation result that we apply to the terms in the first sum is derived in Section A.1. It is used to give us a bound for the differences in probabilities that, for carefully chosen  $\gamma_n \sim n^\epsilon$  and some  $\epsilon > 0$ , allows us to complete the proof.

*A.1. A large deviation result.* We begin by deriving the necessary large deviation results. We start with a large deviation result of Feller (1943) for independent random variables (given in Theorem A.1 for completeness). We note that the  $W$ 's defined in Section 2 ( $S_n = \sum a_{i,n} W_i$ ) are not (in general) independent. However, the  $W$ 's are conditionally independent given  $Z \equiv Z_n = (Z_1, \dots, Z_n)$ . Thus, our first large deviation result in Theorem A.2 involves applying Feller's (1943) theorem to  $(S_n - E(S_n|Z))/(\text{Var}(S_n|Z))^{1/2}$ .

**THEOREM A.1** (Feller (1943), page 363). *Let  $\{Y_k\}$ ,  $k = 1, 2, \dots$ , be independent random variables with  $E(Y_k) = 0$  and  $\text{Var}(Y_k) = \sigma_k^2 < \infty$ . Let  $S_n = Y_1 + \dots + Y_n$  and  $\sigma_n^{*2} = \sigma_1^2 + \dots + \sigma_n^2$ . Finally, let  $F_n(\gamma_n) = \Pr\{S_n \leq \gamma_n\}$  be the distribution function of  $S_n$ .*

*Suppose that  $|Y_k| \leq \lambda_n \sigma_n^*$  for  $k = 1, \dots, n$ . If  $0 < \lambda_n \gamma_n < 1/12$ , then  $|\psi_n| < 9$  and  $1 - F_n(\gamma_n \sigma_n^*) = \exp(-\gamma_n^2 Q_n(\gamma_n)/2) [1 - \Phi(\gamma_n) + \psi_n \lambda_n \exp(-\gamma_n^2/2)]$ , where  $Q_n(\gamma_n) = \sum_{\nu=1}^\infty q_{n,\nu} \gamma_n^\nu$  with  $|q_{n,\nu}| < (12\lambda_n)^\nu/7$  and  $\Phi(\cdot)$  is the cumulative distribution function of the standard normal.*

*In particular, for a uniformly bounded sequence  $\{Y_k\}$ , we have  $\sigma_n^{*2} \sim O(n)$ . Then  $\lambda_n = O(n^{-1/2})$  and, for  $\gamma_n = o(n^{1/6})$ ,  $Q_n(\gamma_n) \rightarrow 0$  and  $\lambda_n \gamma_n = o(n^{-1/3})$ ; thus  $1 - F_n(\gamma_n \sigma_n^*) \sim 1 - \Phi(\gamma_n)$ .*

Before stating and proving our first large deviation result, we state several assumptions.

**ASSUMPTION A.1.** There exists a  $\delta''$ ,  $0 < \delta'' < 1$ , satisfying  $\int_0^{1-\delta''} J^2(u) du > 0$ .

ASSUMPTION A.2. For  $0 < \delta' < \delta'' < 1$  and a sequence of alternatives  $\{\theta_n\}$ ,  $\varepsilon_n$  is positive for all but a finite number of  $n$ , with  $\varepsilon_n = \sup \varepsilon^*$  satisfying  $0 \leq \varepsilon^* \leq \frac{1}{2}$  and

$$\Pr\{\varepsilon^* \leq [f(Y_n - \theta_n)/(f(Y_n - \theta_n) + f(-Y_n - \theta_n))] \leq 1 - \varepsilon^* | \theta_n\} \geq 1 - \delta',$$

where  $Y_n$  is a random variable with density  $f(y - \theta_n)$ .

THEOREM A.2. Given the statistic  $S_n$  with conditions on the scores described in Section 2, Assumptions A.1 and A.2, and  $0 < \gamma_n \lambda_n < 1/12$ , then

$$\begin{aligned} \Pr\{S_n - E(S_n|Z) > \gamma_n \text{Var}(S_n|Z)^{1/2} | \theta_n\} \\ (A.3) \quad &= (1 - \omega_n) \exp(-\gamma_n^2 Q_n(\gamma_n)/2) \\ &\times [\{1 - \Phi(\gamma_n)\} + \psi_n \lambda_n \exp(-\gamma_n^2/2)] + \omega_n \xi_n, \end{aligned}$$

where

$$\begin{aligned} (A.4) \quad \lambda_n &\geq a_{n,n} \left\{ \varepsilon_n (1 - \varepsilon_n) \sum_1^{[n(1-\delta'')] } a_{i,n}^2 \right\}^{-1/2} \\ &\sim J(n/(n+1)) \left\{ \varepsilon_n (1 - \varepsilon_n) n \int_0^{(1-\delta'')} J^2(u) du \right\}^{-1/2}, \end{aligned}$$

$$\begin{aligned} (A.5) \quad |\psi_n| &< 9, \quad Q_n(\gamma_n) = \sum_{\nu=1}^{\infty} q_{n,\nu} \gamma_n^\nu \quad \text{with } |q_{n,\nu}| < (12\lambda_n)^\nu / 7, \\ &0 \leq \omega_n \leq \exp(-2n(\delta' - \delta'')^2) \quad \text{and } 0 \leq \xi_n \leq 1. \end{aligned}$$

PROOF. Let  $g_n(y) = f(y - \theta_n)$  and define  $P_j = g_n(Z_j)/(g_n(Z_j) + g_n(-Z_j))$  for  $j = 1, \dots, n$ . Using Okamoto (1958) (e.g., Albers, Bickel and van Zwet (1976), page 118) yields

$$\begin{aligned} (A.6) \quad \Pr\{\varepsilon_n < P_j < 1 - \varepsilon_n \text{ for at least } (1 - \delta'')n \text{ indices } j\} \\ \geq 1 - \exp(-2n(\delta' - \delta'')^2). \end{aligned}$$

Let  $A_n$  be the event in  $\{ \}$  in (A.6). We next condition on  $Z$ . Define  $p_j = g_n(z_j)/(g_n(z_j) + g_n(-z_j))$  and  $Y_k = a_{k,n}(W_k - p_k)$  where  $Y_k$  is given in Feller's theorem. Then  $E(Y_k|Z) = 0$ ,  $\text{Var}(Y_k|Z) = a_{k,n}^2 p_k q_k$  and  $\text{Var}(\sum Y_k|Z) = \sum a_{k,n}^2 p_k q_k$ . We continue conditioning now on both  $Z$  and the event  $A_n$  to get a bound on the variance

$$\text{Var}\left(\sum Y_k | Z, A_n\right) \geq \varepsilon_n (1 - \varepsilon_n) \sum_1^{n(1-\delta'')} a_{k,n}^2 \sim \varepsilon_n (1 - \varepsilon_n) n \int_0^{1-\delta''} J^2(u) du.$$

Note that by conditioning on  $A_n$ , we are sure that the variance term is going to infinity. Thus, conditioning on  $Z$  and  $A_n$ , we can apply Feller's theorem using (A.4) and (A.5). From (A.6), we note that  $\omega_n = \Pr\{A_n^c\} \leq \exp(-2n(\delta' - \delta'')^2)$  is very small, so that when  $A_n^c$  occurs we only need to use the fact that the large

deviation probability is bounded by one. Unconditioning on  $A_n$  yields (A.6) for some  $0 \leq \xi_n \leq 1$ .  $\square$

Note that Assumption A.1 protects one from having all scores identically zero when looking at the first  $(1 - \delta'')n$  of the scores  $a_{i,n}$ . Assumption (A.2) is given in more generality than is necessary. It includes  $\theta_n = \theta$ , i.e., a fixed alternative, as well as  $\theta_n \rightarrow \theta$ , where  $\liminf \varepsilon_n = \varepsilon > 0$  is bounded away from zero, the two cases in which we are most interested. From the proof of Theorem A.2, we note that we can allow  $\{\theta_n\}$  with the property that  $\liminf \varepsilon_n = 0$  and  $\varepsilon_n > 0$  for all but a finite number of  $n$ .

We are most interested in the contiguous alternative cases where  $\liminf \varepsilon_n = \varepsilon > 0$  and, as we shall see,  $\lambda_n \gamma_n^s = o(1)$  for given  $s > 0$ . We choose  $\lambda_n \sim \{\varepsilon_n(1 - \varepsilon_n)\}^{-1/2} J(n/(n + 1)) n^{-1/2}$ . When  $J(1 - ) < \infty$ , this allows us to choose  $\gamma_n \sim n^\varepsilon$ ,  $0 < \varepsilon < (2s)^{-1}$ . In other cases, we must take into account the rate at which  $J(n/(n + 1)) \rightarrow \infty$ . Recall from Section 2 that we restricted  $|J(u)| \leq K(1 - u)^{\delta-1/2}$ ,  $0 < \delta < \frac{1}{2}$ . For  $J(u) = (1 - u)^{\delta-1/2}$ ,  $0 < \delta \leq \frac{1}{2}$ , we have  $J(n/(n + 1)) \sim n^{1/2-\delta}$ , which suggests using  $\lambda_n \sim Kn^{-\delta}$  and  $\gamma_n \sim n^\varepsilon$ ,  $0 < \varepsilon < \delta/s$ . In the case with  $J(1 - ) < \infty$ , this approach yields  $\delta = \frac{1}{2}$ .

A.2. *Proof of (A.1).* Divide  $\sum_1^{n-n^r}$  in (A.1) into  $\sum_1^{m_n} + \sum_{m_n+1}^{n-n^r}$  and choose  $m_n \rightarrow \infty$  to satisfy  $b_{m_n,n} = \gamma_n \rightarrow \infty$  and  $m_n/n = o(1)$ . Then the first sum (from 1 to  $m_n$ ) in (A.1) in absolute value is less than or equal to

$$(A.7) \quad h^{-r}(n) r m_n^r \max_{m=1, \dots, m_n} |\Pr\{S_{n-m,n} - E(S_{n-m,n}|Z) \geq b_{m,n}(\text{Var}(S_{n-m,n}|Z))^{1/2}\} - \Phi(-b_{m,n})|.$$

Note for  $m \in \{1, \dots, m_n\}$ ,  $b_{m,n} \in [-K, \gamma_n]$ , where  $K$  is a generic positive constant. The condition  $m_n/n = o(1)$  allows us to apply Theorem A.2, which uses  $S_n$  rather than  $S_{n-m_n,n}$ , to bound the term in absolute values in (A.7) by

$$(A.8) \quad \begin{aligned} & \left| [\exp(-b_{m,n}^2 Q_n(b_{m,n})/2) - 1] [1 - \Phi(b_{m,n})] \right| \\ & + |\exp(-b_{m,n}^2 Q_n(b_{m,n})/2) \psi_n \lambda_n \exp(-b_{m,n}^2/2)| \\ & + \omega_n \exp(-b_{m,n}^2 Q_n(b_{m,n})/2) \\ & \times [(1 - \Phi(b_{m,n})) + |\psi_n| \lambda_n \exp(-b_{m,n}^2/2)] + \omega_n \xi_n. \end{aligned}$$

If we choose  $\lambda_n$  and  $\gamma_n$  so that  $0 < \lambda_n \gamma_n < 1/13$  (1/13 rather than 1/12 is used to bound  $12\lambda_n \gamma_n$  below 1 in (A.9)), so that by Theorem A.2,  $|\psi_n| < 9$  and  $|q_{n,\nu}| < (12\lambda_n)^\nu/7$ , then

$$(A.9) \quad \begin{aligned} |Q_n(b_{m,n})| &= \sum_{\nu=1}^{\infty} |q_{n,\nu}| |b_{m,n}|^\nu \leq (1/7) \sum_{\nu=1}^{\infty} (12\lambda_n |b_{m,n}|)^\nu \\ &= (1/7) 12\lambda_n |b_{m,n}| / (1 - 12\lambda_n |b_{m,n}|) \leq K \lambda_n |b_{m,n}| \end{aligned}$$

for  $m \in \{1, \dots, m_n\}$ . Furthermore,

$$(A.10) \quad |b_{m,n}^2 Q_n(b_{m,n})| \leq K \lambda_n |b_{m,n}|^3 \leq K \lambda_n \gamma_n^3.$$

We shall choose  $\gamma_n \rightarrow \infty$  so that  $\lambda_n \gamma_n^3 = o(1)$ . Thus, the last two terms of (A.8) are bounded by  $K \exp\{-2n(\delta' - \delta'')^2\}$ , and the second term in (A.11) is bounded by  $K \lambda_n$ . The second factor of the first term is bounded by one. The first factor of the first term is bounded by  $K \gamma_n^3 \lambda_n$ . Since  $\gamma_n \rightarrow \infty$ , the first two terms of (A.8) substituted into (A.7) are bounded by

$$(A.11) \quad K(m_n/h(n))^r \gamma_n^3 \lambda_n.$$

Using  $b_{m_n, n} = \gamma_n$  and (3.5) yields  $-\gamma_n \approx z_{1-\beta} - b(m_n/h(n))^\eta$ , which can be simplified, recalling that  $\frac{1}{2} < \eta \leq 1$ , to yield

$$(A.12) \quad (m_n/h(n))^r \approx ((\gamma_n + z_{1-\beta})/b)^{r/\eta} \sim K \gamma_n^{r/\eta} \leq K \gamma_n^{2r}.$$

Thus, (A.11) is bounded by  $K \gamma_n^{2r+3} \lambda_n$ , which is  $o(1)$  for  $\gamma_n = n^\epsilon$ ,  $0 < \epsilon < \delta/(2r + 3)$ , and  $r$  a positive integer since  $\lambda_n \sim K n^{-\delta}$ ,  $0 < \delta \leq \frac{1}{2}$ , as noted at the end of Section A.1. The last two terms of (A.8) substituted into (A.7) are bounded by  $K \gamma_n^{2r+3} \exp\{-2n(\delta' - \delta'')^2\}$ , which is  $o(1)$  for our choice of  $\gamma_n$ .

The sum from  $m_n + 1$  to  $n - n^R$  in (A.1) is bounded by  $K h^{-r}(n) n^r \Phi(-\gamma_n)$  since the probability terms are nonincreasing as  $m$  increases, there are fewer than  $n$  terms in the summation, and  $m \leq n$ . For  $\gamma_n = n^\epsilon$ ,  $n^r \Phi(-n^\epsilon) \sim n^r \phi(n^\epsilon)/n^\epsilon = o(1)$ .  $\square$

A.3. *Proof of (A.2).* As in the proof of (A.1), divide  $\Sigma_1^{n-n^R}$  in (A.2) into  $\Sigma_1^{m_n} + \Sigma_{m_n+1}^{n-n^R}$  and choose  $m_n \rightarrow \infty$  to satisfy  $b_{m_n, n} = \gamma_n \rightarrow \infty$  and  $m_n/n = o(1)$ . The second sum from  $m_n + 1$  to  $n - n^R$  can be shown to be  $o(1)$  using the techniques at the end of the proof of (A.1) in Section A.2 We concentrate only on the first sum.

We shall write  $\Pr\{S_n^* \leq x\}$  in terms of the conditional means and variances given  $Z$ . We then restrict our attention to the case  $Z \in A_n$  since  $\Pr\{Z \in A_n'\}$  is negligible for our purposes. After giving some asymptotic expansions of the conditional means and variances for  $\theta_n$  satisfying (3.1) and (3.2), we show that the differences in probabilities in (A.2) for  $m \in \{1, \dots, m_n\}$  are negligible using Theorem A.2. We then use these results to show  $\Sigma_1^{m_n}$  in (A.2) is  $o(1)$ .

We can rewrite  $\Pr\{S_n^* \leq x\}$  in terms of the conditional mean and variance given  $Z$  as

$$(A.13) \quad \begin{aligned} & \Pr\{S_n - E(S_n) \leq x(\text{Var}(S_n))^{1/2}\} \\ &= \Pr\{S_n - E(S_n|Z) \leq (\Delta_1(1 + \Delta_3) + x(1 + \Delta_2))(\text{Var}(S_n|Z))^{1/2}\}, \end{aligned}$$

where

$$\begin{aligned} \Delta_1 &= (E(S_n) - E(S_n|Z))/(E(\text{Var}(S_n|Z)))^{1/2}, \\ 1 + \Delta_2 &= (\text{Var}(S_n)/\text{Var}(S_n|Z))^{1/2}, \end{aligned}$$

and

$$1 + \Delta_3 = \{(E(\text{Var}(S_n|Z)))/\text{Var}(S_n|Z)\}^{1/2}.$$

We first investigate the size of the difference

$$(A.14) \quad \Pr\{S_n - E(S_n) \leq x(\text{Var}(S_n))^{1/2}\} \\ - \Pr\{S_n - E(S_n|Z) \leq x(\text{Var}(S_n|Z))^{1/2}\},$$

assuming  $Z \in A_n$  ( $A_n$  defined in the proof of Theorem A.2). To do this, we need to characterize  $\Delta_1$ ,  $\Delta_2$  and  $\Delta_3$  in (A.13). Given  $Z$ , we expand  $p_i = f(z_i - \theta)/(f(z_i - \theta) + f(-z_i - \theta))$  in a Taylor series in  $\theta_n$  about 0 with  $g(x) = f'(x)/f(x)$  to get

$$(A.15) \quad p_i = 1/2 - (\theta_n/2)g(z_i) - (\theta_n^2/2)[0] + \dots$$

We use (A.15) to obtain the following asymptotic expansions for  $\theta_n$  satisfying (3.1) and (3.2):

$$(A.16) \quad E(S_n|Z) = \sum a_{i,n} p_i \approx \frac{1}{2} \sum a_{i,n} - (\theta_n/2) \sum a_{i,n} g(Z_i) + \dots,$$

$$(A.17) \quad E(S_n) = E[E(S_n|Z)] \approx \frac{1}{2} \sum a_{i,n} - (\theta_n/2) \sum a_{i,n} E(g(Z_i)) + \dots,$$

$$(A.18) \quad \text{Var}(S_n|Z) = \sum a_{i,n}^2 p_i(1 - p_i) \\ \approx \frac{1}{4} \sum a_{i,n}^2 - (\theta_n^2/4) \sum a_{i,n}^2 g^2(Z_i) + \dots,$$

$$(A.19) \quad E[\text{Var}(S_n|Z)] \approx \frac{1}{4} \sum a_{i,n}^2 - (\theta_n^2/4) \sum a_{i,n}^2 E(g^2(Z_i)) + \dots,$$

$$(A.20) \quad \text{Var}[E(S_n|Z)] \approx (\theta_n^2/4) E\left[\sum a_{i,n} (g(Z_i) - E(g(Z_i)))\right]^2 + \dots$$

We also use the well-known expression

$$(A.21) \quad \text{Var}(S_n) = E[\text{Var}(S_n|Z)] + \text{Var}[E(S_n|Z)].$$

We first look at  $\Delta_1$  in (A.13). By Chebyshev's inequality,

$$(A.22) \quad \Pr\{|\Delta_1| \geq d\} \leq \text{Var}[E(S_n|Z)]/(d^2 E(\text{Var}(S_n|Z))), \quad d > 0,$$

which, for  $Z \in A_n$ , is asymptotically less than or equal to  $K\theta_n^2/d^2$  using (A.19) and (A.20). Since  $\theta_n^2 \sim K/n$ , we can choose  $d = n^{-\delta}$ ,  $0 < \delta < \frac{1}{2}$ , to get

$$(A.23) \quad \Pr\{|\Delta_1| \geq n^{-\delta} | Z \in A_n\} \leq K/n^{1-2\delta}.$$

We note that for  $Z \in A_n$ ,  $1 + \Delta_2 \approx 1 + K\theta_n^2$  and  $1 + \Delta_3 \approx 1 + K\theta_n^2$ , using (A.18)–(A.21). Thus, for  $Z \in A_n$ ,  $\Delta_2 \sim K/n$  and  $\Delta_3 \sim K/n$ . The term  $x + \Delta_1 + x\Delta_2 + \Delta_1\Delta_3$  in (A.13), for  $Z \in A_n$  and when  $|\Delta_1| < n^{-\delta}$ ,  $0 < \delta < \frac{1}{2}$  (which occurs asymptotically with probability greater than  $1 - Kn^{2\delta-1}$ ), is of the form:  $x + \Delta_1 + x\Delta_2\Delta_1\Delta_3 \approx x + \Delta$ , with  $\Delta = O(n^{-\delta})$  for  $x/n^{1-\delta} = o(1)$ , where we note that  $x$  may be  $x_n \rightarrow \infty$  (i.e.,  $x_n \sim Kn^\epsilon$  for some small positive  $\epsilon$ ) in some of our applications of these results.

We next investigate the difference in (A.14) for  $Z \in A_n$  and  $|\Delta_1| < n^{-\delta}$ . The difference when we have  $Z \in A'_n$  or  $Z \in A_n$  and  $|\Delta_1| \geq n^{-\delta}$  (to be shown to have negligible probability) will be less than one in absolute value times a negligible probability.

Let  $h_1(x) = (1 - \Phi(x))h_3(x)$  and  $h_2(x) = K\psi_n\lambda_n\phi(x)h_3(x)$ , with  $h_3(x) = \exp\{-x^2Q_n(x)/2\}$ . We first investigate the difference in probability terms for  $m = 1, \dots, m_n$  in [ ] in (A.2), rewritten as in (A.14) using the result of (A.13) for  $Z \in A_n$  and  $|\Delta_1| < n^{-\delta}$ . If we let  $\bar{h}(x) = h_1(x) + h_2(x)$ , we note that the difference in probability terms in (A.14) is of the form  $\bar{h}(x + \Delta) - \bar{h}(x)$ , with  $\Delta \rightarrow 0$  as  $n \rightarrow \infty$  using Theorem A.2. The term involving  $h_2(x)$  is bounded by  $K\lambda_n$  for  $x$  satisfying  $0 < \lambda_n x_n < 1/13$  and  $12\lambda_n x_n = o(1)$ . Thus,

$$|h_2(x + \Delta) - h_2(x)| \leq K|h_2(x)| \leq K\lambda_n.$$

The term

$$|h_1(x + \Delta) - h_1(x)| \leq |h_3(x + \Delta) - h_3(x)| \approx |\Delta||h'_3(x)|$$

for large  $n$ , where

$$h'_3(x) = -h_3(x)[2xQ_n(x) + x^2Q'_n(x)]/2.$$

We bound  $|Q_n(x)| \leq K\lambda_n|x|$  and  $|Q'_n(x)| \leq K\lambda_n$  for  $\lambda_n x = o(1)$  using techniques similar to the derivation of (A.9) and (A.10). Thus,  $|h'_3(x)| \leq Kx^2\lambda_n$  for our sequences of  $x$ 's. Using these results for the differences in probabilities in [ ] in (A.2) for  $m = 1, \dots, m_n$  and the techniques used in the proof of (A.1) for these terms shows (A.2) for  $Z \in A_n$  and  $|\Delta_1| < n^{-\delta}$ .

For the cases where  $Z \in A'_n$  or  $Z \in A_n$  and  $|\Delta_1| \geq n^{-\delta}$ , we bound the differences in probabilities in (A.2) for  $m = 1, \dots, m_n$  by one times a negligible probability, i.e., the probability that  $Z \in A'_n$  or  $Z \in A_n$  and  $|\Delta_1| \geq n^{-\delta}$ . These negligible probabilities are bounded by  $K \exp\{-2(n - m_n)(\delta' - \delta'')^2\}$  (from (A.6)) and  $K(n - m_n)^{2\delta - 1}$  (from (A.23)), respectively. Note that  $m_n/n \rightarrow 0$ , so that the  $m_n$  in these two probability terms can be ignored in the following calculation. Using  $(m_n/h(n))^r \leq K\gamma_n^{2r}$  from (A.12) for  $Z \in A'_n$  and  $m = 1, \dots, m_n$ , we bound the absolute value of (A.2) by  $K\gamma_n^{2r} \exp\{-2n(\delta' - \delta'')^2\} = o(1)$ . For  $Z \in A_n$ ,  $|\Delta_1| \geq n^{-\delta}$ , and  $m = 1, \dots, m_n$ , we bound absolute (A.2) by  $K\gamma_n^{2r}n^{2\delta - 1}$ . Since  $\gamma_n = O(n^\epsilon)$ , with  $\epsilon > 0$  being chosen arbitrarily small, we can choose  $\epsilon$  so this last term is  $o(1)$ .  $\square$

### APPENDIX B

**Justification of (3.14).** The absolute difference between (3.13) and (3.14), by the triangle inequality, is bounded by

$$(B.1) \quad \sum_{m=1}^{m_n} h^{-r}(n)rm^{r-1} \left| \Phi(-b_{m,n}) - \int_m^{m+1} \Phi(-b_{t,n}) dt \right|.$$

We wish to show that this expression is  $o(1)$ . Given any  $\epsilon > 0$ , choose  $m_n^* < m_n$  with the property that  $m_n^*/h(n) \rightarrow \epsilon^{1/r}/r$ . We divide  $\sum_1^{m_n}$  into  $\sum_1^{m_n^*}$  and  $\sum_{m_n^*+1}^{m_n}$  and consider the two parts separately.

Bounding the difference in absolute values by one for  $m = 1, \dots, m_n^*$ , we can bound the first sum by  $(m_n^*/h(n))^r r \rightarrow \epsilon$  and thus it can be made arbitrarily



small. The second sum is bounded by

$$(B.2) \quad r(m_n/h(n))^r \max_{m \in \{m_n^*+1, \dots, m_n\}} |\Phi(-b_{m,n}) - \Phi(-b_{m+1,n})|$$

$$(B.3) \quad \leq r(m_n/h(n))^r \phi(0) \max_{m \in \{m_n^*+1, \dots, m_n\}} |b_{m,n} - b_{m+1,n}|,$$

since the maximum unit change in  $\Phi(x)$  occurs at  $x = 0$ . Using (3.5), for  $m \in \{m_n^* + 1, \dots, m_n\}$ , we have for large  $n$

$$|b_{m,n} - b_{m+1,n}| \simeq K(m/h(n))^\eta ((1 + 1/m)^\eta - 1) \simeq K(m/h(n))^\eta / m.$$

This last expression is bounded for any  $m \in \{m_n^* + 1, \dots, m_n\}$  by

$$K(m_n/h(n))^\eta / m_n^* \sim K(m_n/h(n))^\eta / h(n),$$

noting that  $m_n^* \sim h(n)\varepsilon^{1/r}/r$ . Substitution of this bound into (B.3) yields the bound

$$(B.4) \quad K(m_n/h(n))^{r+\eta} h^{-1}(n) \leq K\gamma_n^{2r}/h(n),$$

letting  $\gamma_n = m_n/h(n)$ . We know that for a score function  $J(u)$  as constrained in Section 2, there exists a  $\pi > 0$  so that  $n^\pi/h(n) = o(1)$  (see, for example, Lemma 4.6). Thus (B.4) is bounded by  $K\gamma_n^{2r}/n^\pi = o(1)$  for  $\gamma_n = n^\varepsilon$ ,  $0 < \varepsilon < \pi/2r$ .  $\square$

## APPENDIX C

**Justification of moving limit under integral sign in (3.15).** Let  $f_n(t) = rt^{r-1}\Phi(-b_{[h(n)t],n})I(h^{-1}(n) \leq t \leq m_n/h(n))$ . To apply the dominated convergence theorem, it suffices to find a  $g(t) \geq 0$  with the properties that (1)  $\int_0^\infty g(t) dt < \infty$  and (2) there exists an  $N$  such that, for all  $n > N$ ,  $|f_n(t)| \leq g(t)$ ,  $0 < t < \infty$ . Since there exists  $\varepsilon > 0$  such that  $m_n/h(n) = o(n^{2\varepsilon})$  and we can choose  $m_n$  so this holds for any small  $\varepsilon > 0$ , we choose  $\varepsilon$  so  $2\varepsilon$  is less than the  $\varepsilon$  needed in the assumptions for (3.5) and (3.6). Note that

$$-b_{[h(n)t],n} = z_{1-\beta} - bt^\eta - t^\eta \{(z_{1-\beta} + b_{[h(n)t],n})/t^\eta - b\}.$$

By the assumptions for (3.5), we know that for  $n > N(b/2)$  the absolute value of the expression in  $\{ \}$  is bounded by  $b/2$  uniformly for all  $t$  satisfying  $h^{-1}(n) < t < Kn^\varepsilon$ . Thus  $-b_{[h(n)t],n} \leq z_{1-\beta} - (b - b/2)t^\eta \leq 2z_{1-\beta} - (b/4)t^\eta$  for  $n > N(b/2)$ . If we choose  $g(t) = rt^{r-1}\Phi(2|z_{1-\beta}| - (b/4)t^\eta)$ , then (1) is satisfied and (2) is satisfied for all  $n > N(b/2)$ .  $\square$

## REFERENCES

- ALBERS, W., BICKEL, P. J. and VAN ZWET, W. R. (1976). Asymptotic expansions for the power of distribution free tests in the one-sample problem. *Ann. Statist.* 4 108-156.
- ALLING, D. W. (1966). Closed sequential test for binomial probabilities. *Biometrika* 53 73-84.
- ANDERSON, T. W. and FRIEDMAN, M. (1960). A limitation of the optimum property of the sequential probability ratio test. In *Contributions to Probability and Statistics* (I. Olkin, S. G. Ghurye, W. Hoeffding, W. G. Madow and H. B. Mann, eds.) 57-69. Stanford Univ. Press.
- ARMITAGE, P. (1975). *Sequential Medical Trials*. Wiley, New York.
- BROWN, L. D., COHEN, A. and STRAWDERMAN, W. E. (1979). On the admissibility or nonadmissibility of fixed sample size tests in a sequential setting. *Ann. Statist.* 7 569-578.

- COHEN, A. C. (1970). Curtailed attribute sampling. *Technometrics* **12** 295–298.
- CRAIG, C. C. (1968). The average sample number for truncated single and double attribute acceptance plans. *Technometrics* **10** 685–692.
- DEMETTS, D. and HALPERIN, M. (1982). Early stopping in the two-sample problem for bounded random variables. *Controlled Clinical Trials* **3** 1–11.
- DEMETTS, D. and LAN, G. (1984). An overview of sequential methods and their application in clinical trials. *Comm. Statist. A—Theory Methods* **13** 2315–2338.
- DWIGHT, H. B. (1961). *Tables of Integrals and Other Mathematical Data*, 4th ed. Macmillan, New York.
- EISENBERG, B. and GHOSH, B. K. (1980). Curtailed and uniformly most powerful sequential tests. *Ann. Statist.* **8** 1123–1131.
- EISENBERG, B. and GHOSH, B. K. (1981). On the sample size of curtailed tests. *Comm. Statist. A—Theory Methods* **10** 2177–2196.
- FELLER, W. (1943). Generalization of a probability theorem of Cramér. *Trans. Amer. Math. Soc.* **54** 361–372.
- GARNER, N. R. (1958). Curtailed sampling for variables. *J. Amer. Statist. Assoc.* **53** 862–867.
- HÁJEK, J. and ŠIDÁK, Z. (1967). *Theory of Rank Tests*. Academic, New York.
- HALPERIN, M. and WARE, J. (1974). Early decision in a censored Wilcoxon two-sample test for accumulating survival data. *J. Amer. Statist. Assoc.* **69** 414–422.
- HERRMANN, N. and SZATROWSKI, T. H. (1980). Expected sample size savings from curtailed procedures for the  $t$ -test and Hotelling's  $T^2$ . *Ann. Statist.* **8** 682–686.
- HERRMANN, N. and SZATROWSKI, T. H. (1982). Asymptotic formulas for expected sample size savings in curtailed binomial tests. *Sequential Anal.* **1** 221–246.
- HERRMANN, N. and SZATROWSKI, T. H. (1985). Curtailed binomial sampling procedures for clinical trials with paired data. *Controlled Clinical Trials* **6** 25–37.
- LAN, G., SIMON, R. and HALPERIN, M. (1982). Stochastically curtailed tests in long-term clinical trials. *Sequential Anal.* **1** 207–219.
- O'BRIEN, P. and FLEMING, T. (1979). A multiple testing procedure for clinical trials. *Biometrics* **35** 549–556.
- OKAMOTO, M. (1958). Some inequalities relating to the partial sums of binomial probabilities. *Ann. Inst. Statist. Math.* **10** 29–35.
- PASTERNAK, B. (1984). A note on data monitoring, incomplete data and curtailed testing. *Controlled Clinical Trials* **5** 217–222.
- PHATAK, A. G. and BHATT, N. M. (1967). Estimation of the fraction defective in curtailed sampling plans by attributes. *Technometrics* **9** 219–228.
- POCOCK, S. J. (1977). Group sequential methods in the design and analysis of clinical trials. *Biometrika* **64** 191–199.
- PURI, M. L. and SEN, P. K. (1971). *Nonparametric Methods in Multivariate Analysis*. Wiley, New York.
- SAMUEL, E. (1970). Randomized sequential tests. A comparison between curtailed single-sampling plans and sequential probability ratio tests. *J. Amer. Statist. Assoc.* **65** 431–437.
- SHAH, D. K. and PHATAK, A. G. (1972). A simplified form of the ASN for a curtailed sampling plan. *Technometrics* **14** 925–929.
- SHAH, D. K. and PHATAK, A. G. (1974). The maximum likelihood estimate of the fraction defective under curtailed multiple sampling plans. *Technometrics* **16** 311–315.
- VERTER, J. I. (1979). Early decision using simple rank statistics for accumulating survival data. Ph.D. thesis, Univ. of North Carolina, Chapel Hill.
- WONG, P. G. and WONG, S. P. (1982). A curtailed test for the slope parameter of the Weibull distribution. *Metrika* **29** 203–209.