# A NOTE ON FIRST EXIT TIMES WITH APPLICATIONS TO SEQUENTIAL ANALYSIS<sup>1</sup>

#### By Tze Leung Lai

### Columbia University

In this paper, we prove certain theorems about the first exit time  $N = \inf\{n \ge 1: S_n T_n + R_n \notin (-a, b)\}$ , where  $S_n$  is the partial sum of i.i.d. random variables with zero mean and finite positive variance, and  $R_n$ ,  $T_n$  are two sequences of random variables satisfying certain conditions. Such exit times arise in the analysis of the stopping rules of invariant sequential probability ratio tests, and our theorems are then applied to study the stopping rules of these tests.

1. Introduction. In recent years, the sample size distribution of invariant sequential probability ratio tests (SPRT) of composite hypotheses have been studied by a number of authors. Wijsman's papers [8], [9], [10] contain an extensive list of references on the subject. Asymptotic approximations for the moments of the stopping rule N have been explicitly evaluated in particular cases. For the rank-order SPRT in the two-sample problem of testing H: F = G versus  $K: F = G^A$ , where  $0 < A \ne 1$  is a known constant, Savage and Sethuraman [6] have shown that given  $\varepsilon > 0$ , there exists  $0 < \rho < 1$  such that

(1) 
$$P[|n^{-1}l_n - S(A, F, G)| \ge \varepsilon] = O(\rho^n)$$

where  $l_n$  is the log likelihood ratio of the rank-order at stage n and

(2) 
$$S(A, F, G) = \log 4A - 2 - \int \log (F(x) + AG(x))(dF(x) + dG(x))$$
.

Since we stop as soon as  $l_n \notin (-a, b)$ , it is easy to see from (1) that if  $S(A, F, G) \neq 0$ , then  $Ee^{tN} < \infty$  for  $t \leq \theta(\theta > 0)$  and as min  $(a, b) \to \infty$ ,

(3) 
$$EN^{\beta} \sim (b/S(A, F, G))^{\beta}$$
 if  $S(A, F, G) > 0$   
 $EN^{\beta} \sim (a/|S(A, F, G)|)^{\beta}$  if  $S(A, F, G) < 0$ 

for any  $\beta > 0$ .

Now let  $X_1, X_2, \cdots$  be i.i.d. random variables with a common distribution P. To test the null hypothesis  $H_0$  that P is  $N(\zeta, \sigma^2)$  with  $\zeta/\sigma = \gamma_0$  versus the alternative hypothesis  $H_1$  that P is  $N(\zeta, \sigma^2)$  with  $\zeta/\sigma = \gamma_1 \ (\gamma_0 \neq \gamma_1)$ , the sequential t-test stops at stage  $N = \inf\{n \geq 1 : \log L_n \notin (-a, b)\}$  where  $L_n$  is the likelihood

Received October 1973; revised November 1974.

<sup>&</sup>lt;sup>1</sup> Research supported by the Public Health Service under Grant No. 5-R01-GM-16895-05. AMS 1970 subject classification. Primary 6245.

Key words and phrases. Invariant sequential probability ratio tests, first exit times, last time, asymptotic behavior of moments, sequential t-test.

ratio of the maximal invariant at stage n. Define

(4) 
$$f(u) = \frac{1}{2}[u + (u^2 + 4)^{\frac{1}{2}}], \quad g(u) = \frac{1}{2}uf(u) + \log f(u)$$

(5) 
$$\Psi(y) = g(\gamma_1 y) - g(\gamma_0 y) - \frac{1}{2} \gamma_1^2 + \frac{1}{2} \gamma_0^2$$

(6) 
$$\tilde{X}_n = n^{-1} \sum_{i=1}^{n} X_i$$
,  $v_n^2 = n^{-1} \sum_{i=1}^{n} X_i^2$ .

Then there exists a constant d such that

$$|\log L_n - n\Psi(\bar{X}_n/v_n)| \leq d, \qquad n = 1, 2, \cdots$$

(cf. [4], [9]). Letting  $\lambda = EX_1/(EX_1^2)^{\frac{1}{2}}$ , we obtain from (7) that if  $0 < E|X_1|^{2(\beta+1)} < \infty$ , then as min  $(a, b) \to \infty$ ,

(8) 
$$EN^{\beta} \sim (b/\Psi(\lambda))^{\beta} \quad \text{if} \quad \Psi(\lambda) > 0$$

$$EN^{\beta} \sim (a/\Psi(\lambda))^{\beta} \quad \text{if} \quad \Psi(\lambda) < 0$$

(cf. [4]).

The asymptotic approximations considered above require the assumption that  $\Psi(\lambda) \neq 0$  for the sequential t-test and that  $S(A, F, G) \neq 0$  for the rank-order SPRT of Savage and Sethuraman. In Section 3 below, we shall examine the situations when  $\Psi(\lambda) = 0$  and S(A, F, G) = 0. We recall that for Wald's SPRT which stops as soon as  $\prod_{i=1}^{n} (f_i(X_i)/f_0(X_i)) \notin (A, B)$  in testing a simple null  $f_0$  versus a simple alternative  $f_1$ , Wald's lemma for squared sums can be applied to find an asymptotic approximation for the expected sample size when  $E \log (f_1(X)/f_0(X)) = 0$ . Unlike the case of Wald's SPRT, the log likelihood ratio of the maximal invariant in the invariant SPRT's considered above fails to be a random walk. Nevertheless, expressing the log likelihood ratio of the maximal invariant as a random walk plus a remainder term and analyzing the order of magnitude of the remainder term, we can obtain the asymptotic distribution and moments of the stopping rule by making use of certain results on first exit times which we develop in Section 2.

## 2. The asymptotic distribution and moments of first exit times.

THEOREM 1. Suppose  $X_1, X_2, \cdots$  are i.i.d. random variables such that  $EX_1 = 0$ ,  $EX_1^2 = \sigma^2 > 0$ . Let  $S_n = X_1 + \cdots + X_n$  and let  $R_n$ ,  $T_n$  be two sequences of random variables. Define  $N = \inf\{n \ge 1 : S_n T_n + R_n \notin (-a, b)\}$ . Let  $\lambda \ne 0$ ,  $0 < \nu < 1$ .

- (i) If  $\lim_{n\to\infty} T_n = \lambda$  a.e. and  $\lim_{n\to\infty} n^{-\frac{1}{2}}R_n = 0$  a.e., then as  $a\to\infty$  and  $b\to\infty$  such that  $a/(a+b)\to\nu$ ,  $\lambda^2\sigma^2(a+b)^{-2}N$  converges in distribution to  $\tau=\inf\{t\ge 0: W(t)\notin (-\nu,1-\nu)\}$ , where W(t),  $t\ge 0$ , is the standard Wiener process.
- (ii) Suppose  $E|X_1|^{2+\eta} < \infty$  for some  $\eta > 0$  and  $EL^{\eta}(\delta, \varepsilon) < \infty$  for some  $\gamma > 0$ ,  $\varepsilon > 0$  and  $\delta < \frac{1}{2}$ , where  $L(\delta, \varepsilon) = \sup\{n \ge 1 : |R_n| \ge n^{\delta} \text{ or } |T_n| \le \varepsilon\} \text{ (sup } \emptyset = 0).$  Then  $EN^{\eta} < \infty$ . If furthermore  $\lim_{n \to \infty} T_n = \lambda$  a.e., then as  $a \to \infty$  and  $b \to \infty$  such that  $a/(a+b) \to \nu$ ,

(9) 
$$EN^{\gamma} \sim (|\lambda|\sigma)^{-2\gamma}(a+b)^{2\gamma}E\tau^{\gamma}.$$

PROOF. Let  $U_n = S_n T_n + R_n$ . If  $\lim_{n\to\infty} T_n = \lambda$  a.e. and  $\lim_{n\to\infty} n^{-\frac{1}{2}} R_n = 0$  a.e.,

then the process  $(r^{-\frac{1}{2}}U_{[rt]}/\lambda\sigma, 0 \le t \le 1)$  converges weakly to  $(W(t), 0 \le t \le 1)$  as  $r \to \infty$ . First assume that  $\lambda > 0$ . Set c = a + b. As  $c \to \infty$ , we have  $a = \nu c(1 + o(1)), b = (1 - \nu)c(1 + o(1))$  and so

$$\begin{split} P[N > (\lambda \dot{\sigma})^{-2} c^2 t] &= P[\max_{s \le t} U_{[(\lambda \sigma)^{-2} c^2 s]} < b, \, \min_{s \le t} U_{[(\lambda \sigma)^{-2} c^2 s]} > -a] \\ &\to P[\max_{s \le t} W(s) < 1 - \nu, \, \min_{s \le t} W(s) > -\nu] = P[\tau > t] \; . \end{split}$$

Hence  $(\lambda \sigma)^2 c^{-2}N$  converges in distribution to  $\tau$ . If  $\lambda < 0$ , then a similar argument shows that  $(\lambda \sigma)^2 c^{-2}N$  converges in distribution to  $\tau^* = \inf\{t \ge 0 : W(t) \notin (-(1-\nu), \nu)\}$ , and obviously,  $\tau$  and  $\tau^*$  have the same distribution.

To prove (ii), we note that the assumption  $EL^r(\delta,\varepsilon)<\infty$  implies  $P[L(\delta,\varepsilon)<\infty]=1$ , and so  $\lim_{n\to\infty}n^{-\frac{1}{2}}R_n=0$  a.e. Hence if  $\lim_{n\to\infty}T_n=\lambda$  a.e., then by (i),  $(\lambda\sigma)^2c^{-2}N$  converges in distribution to  $\tau$  as  $c\to\infty$ . We now show that under the assumptions of (ii), the family  $\{(c^{-2}N)^r,c\ge 1\}$  is uniformly integrable. Let  $M_c=\inf\{n\ge L(\delta,\varepsilon)+1:|S_n|\ge \varepsilon^{-1}(c+n^\delta)\}$ . Then  $N\le M_c$  for a>0, b>0. We shall show that

(10) 
$$\lim_{t\to\infty} \sup_{c\geq c_0} E(c^{-2}M_c)^{\gamma} I_{[M_c>c^2t]} = 0.$$

First we note that

(11) 
$$E(c^{-2}M_c)^{\gamma}I_{[M_c>c^2t]} = t^{\gamma}P[M_c>c^2t] + \gamma \int_{t}^{\infty} u^{\gamma-1}P[M_c>c^2u] du .$$

Let  $k \ge 2$  be an integer such that

(12) 
$$\frac{1}{2}k\eta > \gamma$$
 and  $k(\frac{1}{2} - \delta) > \gamma$ .

For  $u \ge 1$ , defining  $n_i = n_i(u) = [ic^2u/k]$ ,  $i = 1, \dots, k$ ,  $n_0 = 0$  and  $S_1' = S_{n_1}$ ,  $S_i' = S_{n_i} - S_{n_{i-1}}$   $(2 \le i \le k)$ , we have

(13) 
$$P[M_{e} > c^{2}u] \leq P[L(\delta, \varepsilon) + 1 > c^{2}u/2k] + P[|S_{n}| < \varepsilon^{-1}(c + n^{\delta}) \text{ for } c^{2}u \geq n \geq c^{2}u/2k] \\ \leq P[L(\delta, \varepsilon) + 1 > c^{2}u/2k] + \prod_{i=1}^{k} P[|S_{i}'| < 2\varepsilon^{-1}(c + n_{i}^{\delta})].$$

Without loss of generality, we can assume that  $\eta \le 1$ . Then for  $u \ge 1$  and  $c^2 \ge 4k$ , we have  $n_i - n_{i-1} \ge c^2 u/2k \ge 2$ , and so by a theorem of Esseen [2],

$$\begin{split} P[|S_i'| < 2\varepsilon^{-1}(c + n_i^{\delta})] \\ &= P[\sigma^{-1}(n_i - n_{i-1})^{-\frac{1}{2}}|S_i'| < 2\varepsilon^{-1}\sigma^{-1}(n_i - n_{i-1})^{-\frac{1}{2}}(c + n_i^{\delta})] \\ &\leq P[|N(0, 1)| < 2\varepsilon^{-1}\sigma^{-1}(n_i - n_{i-1})^{-\frac{1}{2}}(c + n_i^{\delta})] + \zeta(n_i - n_{i-1})^{-\eta/2} \end{split}$$

where  $\zeta$  is a positive constant. Since  $P[|N(0, 1)| \le x] \le x$  for x > 0, it then follows that for  $u \ge 1$  and  $c^2 \ge 4k$ ,

(14) 
$$\prod_{i=1}^{k} P[|S_{i}'| < 2\varepsilon^{-1}(c + n_{i}^{\delta})]$$

$$\leq \{2\varepsilon^{-1}\sigma^{-1}(c^{2}u/2k)^{-\frac{1}{2}}(c + c^{2\delta}u^{\delta}) + \zeta(c^{2}u/2k)^{-\eta/2}\}^{k}.$$

From (12), it is clear that

(15) 
$$\lim_{t\to\infty} \sup_{c^2\geq k} \left\{ t^{\gamma} (c^2 t)^{-k/2} (c + c^{2\delta} t^{\delta})^k + t^{\gamma} (c^2 t)^{-\gamma k/2} + \int_t^{\infty} u^{\gamma-1} [(c^2 u)^{-k/2} (c + c^{2\delta} u^{\delta})^k + (c^2 u)^{-\gamma k/2}] du \right\} = 0.$$

By assumption,  $EL^{\gamma}(\delta, \varepsilon) < \infty$ , and therefore

(16) 
$$\lim_{t\to\infty} \sup_{e\geq c_0} \left\{ t^{\gamma} P[L(\delta,\varepsilon) + 1 > c^2 t/2k] + \gamma \int_t^{\infty} u^{\gamma-1} P[L(\delta,\varepsilon) + 1 > c^2 u/2k] du \right\} = 0.$$

From (11), (13), (14), (15) and (16), (10) follows immediately. [

THEOREM 2. Let  $X_1, X_2, \cdots$  be i.i.d. random variables such that  $P[X_1 \neq 0] > 0$ . Let  $S_n, R_n, T_n$  and N be defined as in Theorem 1, and define  $L_1(\Delta, \varepsilon) = \sup\{n \geq 1 : |R_n| \geq \Delta \text{ or } |T_n| \leq \varepsilon\}$  (sup  $\emptyset = 0$ ),  $\Delta, \varepsilon > 0$ .

- (i) Suppose there exist  $\theta > 0$ ,  $\Delta > 0$  and  $\varepsilon > 0$  such that  $E \exp(\theta L_1(\Delta, \varepsilon)) < \infty$ . Then N is exponentially bounded, i.e.,  $P[N > n] = O(\rho^n)$  for some  $1 > \rho > 0$ .
- (ii) Let  $\gamma > 0$ . Suppose  $EL_1^{\gamma}(\Delta, \varepsilon) < \infty$  for some  $\Delta > 0$ ,  $\varepsilon > 0$ . Then  $EN^{\gamma} < \infty$ . Suppose furthermore that  $EX_1 = 0$ ,  $EX_1^2 = \sigma^2$  and  $\lim T_n = \lambda$  a.e., where  $\lambda$  is a nonzero constant. Then (9) holds as  $a \to \infty$  and  $b \to \infty$  such that  $a/(a+b) \to \nu$ , where  $0 < \nu < 1$ .

PROOF. Without loss of generality, we can assume a > 0, b > 0 and let c = a + b. Since  $N \le \inf \{n \ge L_1(\Delta, \varepsilon) + 1 : |S_n| \ge \varepsilon^{-1}(c + \Delta)\}$ , we have

(17) 
$$P[N > n] \leq P[L_1(\Delta, \varepsilon) + 1 \geq \frac{1}{2}n] + P[|S_j| < \varepsilon^{-1}(c + \Delta) \text{ for all } \frac{1}{2}n \leq j \leq n] = A_n + B_n, \text{ say.}$$

Since  $P[X_1 \neq 0] > 0$ , we obtain by an argument due to Stein [7] that  $B_n = O(\rho^n)$  for some  $0 < \rho < 1$ . Hence N is exponentially bounded if  $L_1(\Delta, \varepsilon)$  is exponentially bounded, and  $EN^{\gamma} < \infty$  if  $EL_1^{\gamma}(\Delta, \varepsilon) < \infty$ .

Now suppose that  $EX_1 = 0$  and  $EX_1^2 = \sigma^2 > 0$ . For c > 0, define  $M_c = \inf\{n \ge L_1(\Delta, \varepsilon) + 1 : |S_n| \ge c\}$ . By the central limit theorem, we can choose  $c_0 > 1$  such that for all  $c \ge c_0$ ,  $P[S_{[\sigma^2]} \ge 2c] \ge p > 0$ . We shall now show that for  $n = 1, 2, \cdots$  and  $c \ge c_0$ ,

(18) 
$$P[M_c \geq 2c^2n] \leq (1-p)^n + P[L_1(\Delta, \varepsilon) + 1 \geq n].$$

For  $n \ge 1$  and  $c \ge c_0$ , define  $n_i = [c^2n] + i[c^2]$ ,  $i = 1, 2, \cdots$  and set  $S_1' = S_{n_1}$ ,  $S_i' = S_{n_i} - S_{n_{i-1}}$ . We note that

(19) 
$$P[|S_j| < c \text{ for } c^2n \le j \le 2c^2n] \le P[|S_i'| < 2c \text{ for } i = 1, \dots, n]$$
  
=  $\prod_{i=1}^n P[|S_i'| < 2c] \le (1-p)^n$ .

Since  $P[M_c \ge 2c^2n] \le P[L_1(\Delta, \varepsilon) + 1 \ge n] + P[|S_j| < c \text{ for } c^2n \le j \le 2c^2n]$  for c > 1, (18) follows easily from (19). From (18), it is clear that if  $EL_1^{\gamma}(\Delta, \varepsilon) < \infty$ , then the family  $\{(c^{-2}M_c)^{\gamma} : c \ge c_0\}$  is uniformly integrable, and so if  $\lim_{n\to\infty} T_n = \lambda$  a.e., then the asymptotic formula (9) holds.  $\square$ 

3. Applications to invariant sequential probability ratio tests. For the sequential t-test described in Section 1, we stop at stage

$$(20) N = \inf\{n \ge 1 : \log L_n \notin (-a, b)\}$$

where  $L_n$  is the likelihood ratio of the maximal invariant based on the first n observations  $X_1, \dots, X_n$  and satisfies (7). Let  $\mu = EX_1, \rho^2 = EX_1^2, \lambda = \mu/\rho$  and suppose that  $\Psi(\lambda) = 0$ . We note that  $\Psi$  is of class  $C^{\infty}$  and  $\Psi'(y) \neq 0$  for all y (cf. [9]). Therefore

$$n\Psi(\bar{X}_n/v_n) = n(\bar{X}_n/v_n - \lambda)\Psi'(\hat{\lambda}_n) = (\sum_{i=1}^n X_i - n\lambda v_n)\Psi'(\hat{\lambda}_n)/v_n$$

where  $\hat{\lambda}_n$  lies between  $\bar{X}_n/v_n$  and  $\lambda$ . Furthermore,

$$v_n = (n^{-1} \sum_{i=1}^{n} X_i^2)^{\frac{1}{2}} = \rho + (n^{-1} \sum_{i=1}^{n} X_i^2 - \rho^2)/2\hat{\rho}_n$$

with  $\hat{\rho}_n$  lying between  $v_n$  and  $\rho$ . Hence

$$n\Psi(\bar{X}_{n}/v_{n}) = (\Psi'(\hat{\lambda}_{n})/v_{n})\{(\sum_{1}^{n} X_{i} - n\mu) - \lambda(\sum_{1}^{n} X_{i}^{2} - n\rho^{2})/2\hat{\rho}_{n}\}$$

$$= \{\Psi'(\hat{\lambda}_{n})/(\hat{\rho}_{n}v_{n})\}\{\hat{\rho}_{n}(\sum_{1}^{n} X_{i} - n\mu) - \frac{1}{2}\lambda(\sum_{1}^{n} X_{i}^{2} - n\rho^{2})\}$$

$$= T_{n}\{(\sum_{1}^{n} Y_{i} - nEY_{1}) + (\hat{\rho}_{n} - \rho)(\sum_{1}^{n} X_{i} - n\mu)\}$$

where  $T_n = \Psi'(\hat{\lambda}_n)/(\hat{\rho}_n v_n)$ ,  $Y_i = \rho X_i - \frac{1}{2}\lambda X_i^2$  and so  $EY_1 = \frac{1}{2}\rho\mu$ . Hence letting

(21) 
$$R_n = (\log L_n - n\Psi(\bar{X}_n/v_n)) + T_n(\hat{\rho}_n - \rho)(\sum_{i=1}^n X_i - n\mu),$$

we have

(22) 
$$\log L_n = T_n \sum_{i=1}^n (Y_i - EY_1) + R_n.$$

By making use of Theorem 1, we can then obtain the asymptotic distribution and moments of N.

THEOREM 3. Suppose  $X_1, X_2, \cdots$  are i.i.d. random variables such that  $EX_1 = \mu$ ,  $EX_1^2 = \rho^2$  and

(23) 
$$P[\rho X_1 - \frac{1}{2}\lambda X_1^2 = \frac{1}{2}\rho\mu] < 1$$

where  $\lambda = \mu/\rho$  and suppose that  $\Psi(\lambda) = 0$  with  $\Psi$  defined by (5). Assume that  $E|X_1|^{2p} < \infty$  for some p > 2. Let N be defined by (20), and let  $\Phi$  denote the distribution function of the standard normal distribution. Set  $\sigma^2 = E(\rho X_1 - \frac{1}{2}\lambda X_1^2 - \frac{1}{2}\rho\mu)^2$ . Then for any  $0 < \nu < 1$ , we have as  $a \to \infty$  and  $b \to \infty$  such that  $a/(a + b) \to \nu$ ,

(24) 
$$P[N > (\sigma \rho^{-2} \Psi'(\lambda))^{-2} (a+b)^{2} t] \\ \rightarrow \sum_{k=-\infty}^{\infty} \{ \Phi(t^{-\frac{1}{2}} (2k+1-\nu)) - \Phi(t^{-\frac{1}{2}} (2k-\nu)) \\ - \Phi(t^{-\frac{1}{2}} (2k+1+\nu)) + \Phi(t^{-\frac{1}{2}} (2k+\nu)) \} \\ = U(t), \quad say;$$

(25) 
$$EN^{\beta} \sim \beta(a+b)^{2\beta} \rho^{4\beta} |\sigma \Psi'(\lambda)|^{-2\beta} \int_0^{\infty} t^{\beta-1} U(t) dt$$
 for  $0 < \beta < p-1$ .

LEMMA (cf. [1]). Let  $Z_1, Z_2, \cdots$  be i.i.d. random variables such that  $EZ_1 = 0$  and  $E|Z_1|^p < \infty$ . Let  $M(\alpha, \varepsilon) = \sup\{n \ge 1 : |\sum_{i=1}^n Z_i| \ge \varepsilon n^{\alpha}\}$  (sup  $\emptyset = 0$ ). Then  $EM^{p\alpha-1}(\alpha, \varepsilon) < \infty$  for all  $\varepsilon > 0$  and all  $\alpha > \frac{1}{2}$  with  $p\alpha > 1$ .

PROOF OF THEOREM 3. First note that  $\sigma^2 = \text{Var } Y_1 > 0$  by (23) and  $E|Y_1|^p < \infty$  with p > 2. Let  $M_1(\varepsilon) = \sup\{n \ge 1 : |v_n|^2 - \rho^2| \ge \varepsilon \text{ or } |\bar{X}_n - \mu| \ge \varepsilon\}$ . Then

since  $E|X_1|^{2p} < \infty$ ,  $EM_1^{p-1}(\varepsilon) < \infty$  for all  $\varepsilon > 0$  by the preceding lemma. It then follows that  $EM_2^{p-1}(\varepsilon) < \infty$  for all  $\varepsilon > 0$ , where  $M_2(\varepsilon) = \sup\{n \ge 1: |T_n - \rho^{-2}\Psi'(\lambda)| \ge \varepsilon\}$ . For  $0 < \beta < p-1$ , we can choose  $\alpha > \frac{1}{2}$  such that  $\beta < p\alpha - 1$  and  $\alpha < 1$ . Let  $\gamma = 1 - \alpha$  and choose  $0 < \zeta < \gamma$ . Define

$$M_3(\gamma, \varepsilon) = \sup \{ n \ge 1 : |v_n^2 - \rho^2| \ge \varepsilon n^{-\gamma} \} = \sup \{ n \ge 1 : |\sum_{1}^n X_i^2 - n\rho^2| \ge \varepsilon n^{\alpha} \}.$$

Since  $E|X_1|^{2p}<\infty$ , it follows from the preceding lemma that  $EM_3^{p\alpha-1}(\gamma,\varepsilon)<\infty$  and so  $EM_3^{\beta}(\gamma;\varepsilon)<\varepsilon$  for all  $\varepsilon>0$ . Therefore  $EM_4^{\beta}(\gamma,\varepsilon)<\infty$  for all  $\varepsilon>0$ , where we define

$$\begin{aligned} M_{4}(\gamma, \varepsilon) &= \sup \left\{ n \geq 1 : |\hat{\rho}_{n} - \rho| \geq \varepsilon n^{-\gamma} \right\}; \\ M_{5}(\zeta, \varepsilon) &= \sup \left\{ n \geq 1 : |\sum_{i=1}^{n} X_{i} - n\mu| \geq \varepsilon n^{\frac{1}{2} + \zeta} \right\}. \end{aligned}$$

By the preceding lemma, we obtain that  $EM_5^{2p(\frac{1}{2}+\zeta)-1}(\zeta,\varepsilon)<\infty$  and so  $EM_5^{\beta}(\zeta,\varepsilon)<\infty$  for all  $\varepsilon>0$ . Let  $\delta=\frac{1}{2}+\zeta-\gamma$ . Then  $\delta<\frac{1}{2}$ . Define  $M_6(\delta)=\sup\{n\geq 1:|R_n|\geq n^\delta\}$ . Using the finiteness of  $EM_2^{\beta}(\varepsilon)$ ,  $EM_4^{\beta}(\gamma,\varepsilon)$  and  $EM_5^{\beta}(\zeta,\varepsilon)$ , we obtain from (7) and (21) that  $EM_6^{\beta}(\delta)<\infty$ . From (22), Theorem 1 is applicable to N, and noting that  $P[\tau>t]=U(t)$  (cf. [3], page 329), where  $\tau$  is as defined in Theorem 1, we obtain the asymptotic formulas (24) and (25) from Theorem 1.  $\square$ 

Theorem 1 can similarly be used to study the stopping time of the rankorder SPRT of Savage and Sethuraman in the case when S(A, F, G) = 0, where S(A, F, G) is defined by (2), since here we again have the representation of the log likelihood ratio  $l_n$  in terms of the partial sum of i.i.d. random variables plus a remainder term whose order of magnitude we can analyze. This representation, which is a special case of a more general representation theorem for generalized Chernoff-Savage statistics, together with related results on other sequential rank tests, will be treated in [4].

#### REFERENCES

- [1] Chow, Y. S. and Lai, T. L. (1973). Some one-sided theorems on the tail distribution of sample sums with applications to the last time and largest excess of boundary crossings. To appear in *Trans. Amer. Math. Soc.* 174.
- [2] ESSEEN, C. G. (1945). Fourier analysis of distribution functions. Acta Math. 77 1-125.
- [3] FELLER, W. (1966). An Introduction to Probability Theory and Its Applications, 2. Wiley, New York.
- [4] Lai, T. L. (1975). On Chernoff-Savage statistics and sequential rank tests. Ann. Statist. 3 825-845.
- [5] LAI, T. L. (1975). Termination, moments and exponential boundedness of the stopping rule for certain invariant sequential probability ratio tests. *Ann. Statist.* 3, 581-598.
- [6] SAVAGE, I. R. and SETHURAMAN, J. (1966). Stopping time of a rank-order sequential test based on Lehmann alternatives. *Ann. Math. Statist.* 37 1154-1160.
- [7] Stein, C. (1946). A note on cumulative sums. Ann. Math. Statist. 17 498-499.
- [8] WIJSMAN, R. A. (1970). Examples of exponentially bounded stopping time of invariant sequential probability ratio tests when the model may be false. *Proc. Sixth. Berkeley Symp. Math. Statist. Prob.* 1 109-128.

- [9] WIJSMAN, R. A. (1971). Exponentially bounded stopping time of sequential probability ratio tests for composite hypotheses. Ann. Math. Statist. 42 1859-1869.
- [10] WIJSMAN, R. A. (1972). A theorem on obstructive distributions. Ann. Math. Statist. 43 1709-1715.

DEPT. OF MATHEMATICAL STATISTICS COLUMBIA UNIVERSITY NEW YORK, NEW YORK 10027