## A SEQUENTIAL PROBABILITY RATIO TEST USING A BIASED COIN DESIGN

## By Nancy E. Heckman<sup>1</sup>

State University of New York at Stony Brook

Consider a sequential probability ratio test comparing two treatments, where each subject receives only one of the treatments. Each subject's treatment assignment is determined by the flip of a biased coin, where the bias serves to balance the number of patients assigned to each treatment. The asymptotic properties of this test are studied, as the sample size approaches infinity. A renewal theorem is given for the joint distribution of the sample size, the imbalance in treatment assignment at the end of the experiment, and the excess over the stopping boundary. This theorem is used to calculate asymptotic expressions for the test's error probabilities.

1. Introduction. In a clinical trial in which two treatments are to be compared, the determination of a suitable method of assigning treatments is an important design problem. It is usually desirable to assign an equal number of subjects to each treatment and to do so in a random manner, to diminish the possibility of bias in the comparison. If subjects arrive one at a time, as in a sequential test, achieving both balance and randomization may be difficult. Efron (1971) and Wei (1978) have proposed the use of a biased coin design: the treatment received by the (n + 1)st subject is determined by the flip of a coin which is biased in favor of the treatment to which fewer of the n previous subjects have been assigned. In this paper I study a sequential probability ratio test (SPRT) in which Wei's biased coin design is used. The SPRT's asymptotic properties are studied as the sample size approaches infinity.

The asymptotic properties of a SPRT are well known in the case of i.i.d. observations (cf. Woodroofe, 1982) and in the case of "almost" i.i.d. observations (Lai and Siegmund, 1977). However, in a biased coin design, the observations are in general not i.i.d., nor are they close enough to those in the i.i.d design (flipping a fair coin to determine treatment assignment) to apply the existing theory.

The allocation scheme and the SPRT are defined in Section 2, and the type I and type II error probabilities are expressed in terms of a type of random walk and a stopping time. Section 3 contains a local limit theorem for the joint distribution of the stopping time, the imbalance in assignment at the time of stopping, and the excess over the stopping boundary. This limit theorem is then used to calculate asymptotic expressions for the error probabilities of the SPRT. Sketches of the proofs are given. For details, see Heckman (1982).

Received August 1983; revised August 1984.

<sup>&</sup>lt;sup>1</sup> Research supported by Veterans Administration Health Services Research and Development Predoctoral Fellowship.

AMS 1980 subject classifications. Primary 62L05, 60K05.

 $<sup>\</sup>it Key words \ and \ phrases.$  Sequential probability ratio test, biased coin design, clinical trial, renewal theory.

**2.** A sequential probability ratio test. Let  $V_i$  and  $W_i$  denote the *i*th subject's responses to the two treatments. Assume that  $(V_i, W_i)$ ,  $i \ge 1$ , are independent and identically distributed and  $V_1$  has distribution function F and  $W_1$  has distribution function G. By observing only one response per patient, we will test

$$H_0: F = F_0, G = G_0 \text{ versus } H_1: F = F_1, G = G_1$$

where  $F_0$  and  $F_1$  are mutually absolutely continuous, as are  $G_0$  and  $G_1$ , with  $F_0 \neq F_1$ ,  $G_0 \neq G_1$ . The allocation procedure is defined as follows. Let  $U_i$ ,  $i \geq 1$ , be i.i.d., uniformly distributed on [0, 1] with  $\{U_i\}$   $i \geq 1$  and  $\{(V_i, W_i)\}$   $i \geq 1$  independent. Let h be a function from [-1, 1] to [0, 1] satisfying:

- (i) h is nonincreasing,
- (ii) h(x) = 1 h(-x),
- (iii)  $h(x) = \frac{1}{2} + h'(0)x + B(x)x^2$  where  $\sup_{|x| \le 1} |B(x)| < \infty$ .

Let  $D_0 = 0$ . Let  $\delta_{n+1} = 1$  if  $U_{n+1} \le h(D_n/n)$ , zero otherwise, where  $D_n = \sum_{i=1}^{n} (2\delta_i - 1)$ . If  $\delta_i = 1$ , we observe  $V_i$ , otherwise we observe  $W_i$ . With this allocation procedure, the *n*th log likelihood ratio statistic for testing  $H_0$  versus  $H_1$  is

(2.1) 
$$S_n = \sum_{i=1}^{n} \delta_i X_i + (1 - \delta_i) Y_i$$

where  $X_i = \log dF_1(V_i)/dF_0$  and  $Y_i = \log dG_1(W_i)/dG_0$ .

Assume that  $X_i$  and  $Y_i$  have finite positive variance under  $H_0$  and  $H_1$ . For a and b positive, let

$$T = T(a, b) = \inf\{n: S_n > a \text{ or } S_n < -b\}.$$

Since the expectations of  $X_1$  and  $Y_1$  are negative under  $H_0$  and positive under  $H_1$ , T is finite almost surely under both hypotheses. The SPRT with boundaries a and b continues testing until T subjects have entered the trial, rejecting  $H_0$  if, at that time,  $S_n > a$  and rejecting  $H_1$  if  $S_n < -b$ .

Suppose that  $(U_i, V_i, W_i)$ ,  $i \ge 1$ , are defined in the probability space  $(\Omega, \mathcal{F}, P)$  and that under  $H_0, P = P_0$  and under  $H_1, P = P_1$ . Let  $\mathcal{F}_{\infty}$  be the sigma algebra generated by  $\delta_i X_i + (1 - \delta_i) Y_i$ ,  $i \ge 1$ .  $\mathcal{F}_n$  is the sigma algebra generated by  $\delta_i X_i + (1 - \delta) Y_i$ ,  $1 \le i \le n$ . Let

$$\mathscr{T}_T = \{A \in \mathscr{T}_{\infty} : A \cap \{T = n\} \in \mathscr{T}_n \text{ for all } n\}$$

and

$$P_i^T = P_i$$
 restricted to  $\mathcal{F}_T$ ,  $i = 0$  or 1.

Then, the probability of a type I error is

$$P_0\{S_T > a\} = \int_{\{S_T > a\}} (dP_0^T/dP_1^T) dP_1$$

$$= \int_{\{S_T > a\}} \exp(-S_T) dP_1.$$

Let

(2.2) 
$$t = t(a) = \inf\{n: S_n > a\}$$
 and  $R_a = S_t - a$ .

t is finite almost surely  $P_1$ . Since  $\{S_T > a\} \subset \{t = T, S_t = S_T\}$  and  $P_1\{S_T > a\} \rightarrow 1$  as a and b approach infinity,

$$P_0\{S_T > a\} \sim \exp(-a) \int \exp(-R_a) dP_1.$$

Thus, determination of the asymptotic distribution of  $R_a$  gives an asymptotic expression for the type I error probability. An asymptotic expression for the type II error probability can be calculated in the same way.

Let

(2.3) 
$$\delta_i^0 = 1 \quad \text{if} \quad U_i \le \frac{1}{2}, \quad \text{zero othèrwise,}$$

$$S_n^0 = \sum_{i=1}^n \delta_i^0 X_i + (1 - \delta_i^0) Y_i,$$

$$\mu = (EX_1 + EY_1)/2.$$

THEOREM 1. If  $X_1 + Y_2$  is nonlattice, then

$$P_0\{reject\ H_0\} \sim \gamma_1 \exp(-a)$$

$$P_1\{reject\ H_1\} \sim \gamma_0 \exp(-b)$$

as a and b approach infinity, where

$$\gamma_i = \mu^{-1} \int_0^\infty \exp(-r) P_i \{ c_i S_j^0 \ge r \text{ for all } j \ge 1 \} dr, \quad i = 0 \quad \text{or} \quad 1,$$

with  $c_0 = -1$  and  $c_1 = 1$ .

The Theorem follows directly from Theorem 2 of Section 3.

3. A renewal theorem. Let h,  $U_i$ ,  $\delta_i$ , and  $D_n$  be as defined in Section 2. Let  $(X_i, Y_i)$ ,  $i \ge 1$ , be i.i.d. with the expectations of  $X_1$  and  $Y_1$  positive, and their variances positive and finite. Suppose that  $\{U_i\}_{i\ge 1}$  and  $\{(X_i, Y_i)\}_{i\ge 1}$  are independent. Let  $S_n$ , t(a),  $R_a$ ,  $\delta_i^0$ ,  $S_n^0$ , and  $\mu$  be as defined in 2.1 to 2.3. Let  $\Delta = (EY_1 - EX_1)/2$ ,  $\sigma^2 = (\text{var } X_1 + \text{var } Y_1)/2$ , and  $g_a(m, n, A) = P\{t(a) = n, D_t = m, R_a \in A\}$  where A is a subinterval of the reals and m - n is an even integer. Suppose that m, n, and n approach infinity in such a manner that

(3.1) 
$$n - a/\mu \sim x(a/\mu)^{1/2}$$
$$m \sim yn^{1/2}$$

where  $-\infty < x$ ,  $y < \infty$ .

THEOREM 2. If  $X_1 + Y_2$  is nonlattice, then

$$\lim_{a\to\infty} ng_a(m, n, A) = \mu\sigma^{-1}\phi((\Delta y - \mu x)/\sigma)2\tau^{-1}\phi(y/\tau) \int_A p(r) dr$$

where

$$p(r) = \mu^{-1} P\{S_i^0 \ge r \text{ for all } j \ge 1\} I\{r \ge 0\},$$

 $\phi$  is the standard normal density, and  $\tau^2 = (1 - 4h'(0))^{-1}$ .

Therefore  $((t - a/\mu)(a/\mu)^{-1/2}, t^{-1/2}D_t, R_a)$  converges in distribution to  $((\Delta D - \sigma S)/\mu, D, R)$  where D, S, and R are independent, D and S are normally distributed with zero means and variances one and  $\tau^2$ , respectively, and R has density p(r).

It is now easy to see the effect of the allocation scheme on the stopping rule. For example, suppose that  $\Delta$  is positive, that is EY > EX. Then the mean of  $(\Delta D - \sigma S)/\mu$  given D is positive if and only if there has been an imbalance in favor of the  $X_i$ 's. Observing an excess of the responses with smaller means causes the test to stop later than expected.

Let  $0 \le r_1 < r_2 < \infty$ . Write

$$g_a(m, n, (r_1, r_2]) = P\{S_n \in a + (r_1, r_2], S_{n-j} \le a, 1 \le j \le n, D_n = m\},\$$

Thus,

$$\underline{f}_a(r_2) \leq g_a(m, n, r_1, r_2) \leq \overline{f}_a(r_1)$$

where

$$\overline{f}_a(r) = P\{S_n \in a + (r_1, r_2], S_n - S_{n-j} > r, 1 \le j \le n - 1, D_n = m\}.$$

and

$$\underline{f}_a(r) = P\{S_n \in a + (r_1, r_2], S_n - S_{n-j} \ge r, 1 \le j \le n - 1, D_n = m\}.$$

Theorem 2 follows directly from Proposition 1 below, the theory of Riemann integration, and the fact that

$$\int_A P\{S_j^0 \ge r \text{ for all } j \ge 1\} \ dr = \int_A P\{S_j^0 > r \text{ for all } j \ge 1\} \ dr.$$

Proposition 1.

$$\lim_{a\to\infty} n\underline{f}_a(r) = (r_2 - r_1)\mu^{-1}P\{S_j^0 \ge r \text{ for all } j \ge 1\}$$

$$\cdot \mu\sigma^{-1}\phi((\Delta y - \mu x)/\sigma)2\tau^{-1}\phi(y/\tau)$$

$$\lim_{a\to\infty} n\overline{f}_a(r) = (r_2 - r_1)\mu^{-1}P\{S_j^0 > r \text{ for all } j \ge 1\}$$

$$\cdot \mu\sigma^{-1}\phi((\Delta y - \mu x)/\sigma)2\tau^{-1}\phi(y/\tau).$$

The proof of the proposition is sketched here. For a more detailed proof, see Heckman (1982). Let

$$\hat{S}_{j} = S_{n}^{0} - S_{n-j}^{0}$$

$$\hat{D}_{i} = \sum_{n-j+1}^{n} (2\delta_{i}^{0} - 1) = D_{n}^{0} - D_{n-j}^{0}.$$

Then

$$\underline{f}_{a}(r) = P\{S_{n-k} + \hat{S}_{k} \in a + (r_{1}, r_{2}], \, \hat{S}_{j} \ge r \text{ for all } j \le k, \, D_{n-k} + \hat{D}_{k} = m\} + \varepsilon(a, k)$$

where  $\lim_{k\to\infty} \lim \sup_{a\to\infty} n \mid \varepsilon(a, k) \mid = 0$ .

Conditioning on  $(\hat{D}_k, \hat{S}_k)$  and using the independence of  $\{\hat{D}_k, \hat{S}_j, j \leq k\}$  and  $\{D_{n-k}, S_{n-k}\}$  and the stationarity of the process  $\{S_j^0\}$ , the first term on the right-hand side of the above equation is equal to

$$\int_{s \ge r, |\mathcal{L}| \le k} P\{S_{n-k} \in a - s + (r_1, r_2] \mid D_{n-k} = m - \mathcal{L}\} P\{D_{n-k} = m - \mathcal{L}\}$$

$$\cdot P\{S_j^0 \ge r \text{ for all } j \le k - 1 \mid D_k^0 = \mathcal{L}, S_k^0 = s\} \ dP\{D_k^0 \le \mathcal{L}, S_k^0 \le s\}$$

By a modified version of Stone's theorem (1965) and Theorem 1 of Heckman (1985)

$$\lim_{a\to\infty} nP\{S_{n-k} \in a - s + (r_1, r_2] | D_{n-k} = m - \ell\} P\{D_{n-k} = m - \ell\}$$
$$= (r_2 - r_1)\sigma^{-1}\phi((\Delta y - \mu x)/\sigma)2\tau^{-1}\phi(y/\tau)$$

if 
$$n-k-(m-\ell)$$
 and

$$\sup_{s \geq r, |\mathcal{L}| \leq k} n P\{S_{n-k} \in a - s + (r_1, r_2] \mid D_{n-k} = m - \mathcal{L}\} P\{D_{n-k} = m - \mathcal{L}\} < \infty$$

The proposition then follows by the dominated convergence theorem.

4. Remarks. Analogues of Theorems 1 and 2 also hold in the following case. Suppose that  $X_1$ ,  $Y_1$ , and  $X_1 + Y_2$  are arithmetic with the arithmetic spans of  $X_1$  and  $Y_1$  integer multiples of the arithmetic span of  $X_1 + Y_2$ . Suppose that the arithmetic and lattice span of  $X_1 + Y_2$  are both equal to  $\lambda$ . (The arithmetic span of a random variable Z is the largest  $\lambda$  such that  $\sum_{-\infty}^{\infty} P\{Z = k\lambda\} = 1$ . The lattice span of Z is the largest  $\lambda$  such that  $\sum_{-\infty}^{\infty} P\{Z = b + k\lambda\} = 1$  for some b. The two types of spans are not necessarily equal.) Then, if m, n, and a satisfy (3.1) and a approaches infinity through multiples of  $\lambda$ ,

$$nP\{t=n, D_n=m, R_a=J\lambda\} \rightarrow \mu\sigma^{-1}\phi((\Delta y-\mu x)/\sigma)2\tau^{-1}\phi(y/\tau)\lambda p(J\lambda)$$

where p is as defined in Theorem 2. Thus, Theorem 1 holds with

$$\gamma_i = \lambda \mu^{-1} \sum_{J=1}^{\infty} P\{c_i S_j^0 \ge J \lambda \text{ for all } j \ge 1\}.$$

Acknowledgments. I am grateful to Michael Woodroofe for his guidance in this research and to Robert Keener for his helpful comments.

## REFERENCES

EFRON, B. (1971). Forcing a sequential experiment to be balanced. *Biometrika* **58** 403–417. HECKMAN, N. (1982). Two treatment comparison with random allocation rule. Ph.D. thesis, University of Michigan.

- HECKMAN, N. (1985). A local limit theorem for a biased coin design for sequential tests. *Ann. Statist.* 13 785–788.
- LAI, T. L. and SIEGMUND, D. (1977). A nonlinear renewal theory with applications to sequential analysis I. Ann. Statist. 5 946-954.
- STONE, C. (1965). A local limit theorem for nonlattice multidimensional distribution functions. *Ann. Math. Statist.* **36** 546–551.
- WEI, L. J. (1978). The adaptive biased coin design for sequential experiments. Ann. Statist. 6 92-100.
- WOODROOFE, M. B. (1982). Nonlinear Renewal Theory in Sequential Analysis. SIAM, Philadelphia.

DEPARTMENT OF APPLIED MATHEMATICS AND STATISTICS STATE UNIVERSITY OF NEW YORK AT STONY BROOK LONG ISLAND, NY 11794