

HETEROGENEITY OF ERROR VARIANCES

IN A

RANDOMIZED BLOCK DESIGN

By

JOHN LEROY FOLKS

Bachelor of Arts

Oklahoma Agricultural and Mechanical College

Stillwater, Oklahoma

1953

Submitted to the faculty of the Graduate School of
the Oklahoma Agricultural and Mechanical College
in partial fulfillment of the requirements

for the degree of
MASTER OF SCIENCE

May, 1955

OKLAHOMA
AGRICULTURAL & MECHANICAL COLLEGE
LIBRARY
OCT 26 1955

HETEROGENEITY OF ERROR VARIANCES
IN A
RANDOMIZED BLOCK DESIGN

Thesis Approved:

Franklin Graybill
Thesis Adviser
R. B. Deaf
Herbert Scholz
J. Wayne Johnson
Lawrence Martin
Dean of the Graduate School

349816

PREFACE

In a randomized block experiment we frequently wish to test the hypothesis that all the treatment means are equal. When we have heterogeneity of error variances, the ratio of the treatment mean square to the error mean square is not distributed as Snedecor's F . An exact method for testing the treatment means equal when we have heterogeneity of error variances has been given by Graybill.

Consider a randomized block experiment with b blocks and $n_1 + n_2$ treatments where the error variance is σ_1^2 for the first n_1 treatments and is σ_2^2 for the next n_2 treatments. The method given by Graybill requires inversion of a matrix of order $n_1 + n_2 - 1$ and is subject to the restriction that $b > n_1 + n_2 - 1$. The method proposed in this paper does not require inversion of a matrix and is subject to the restriction that $b > 2$. In addition, the method proposed in this paper seems to be more powerful than the method proposed by Graybill.

In general, when we have K subsets of treatments such that the first subset has error variance σ_1^2 , the next subset has error variance σ_2^2 , etc., the method proposed in this paper requires inversion of a smaller matrix and is subject to a less stringent restriction than the method proposed by Graybill.

Indebtedness is acknowledged to Dr. Franklin Graybill for suggesting this problem to me, and for his help during the preparation of this paper.

TABLE OF CONTENTS

INTRODUCTION	1
TEST CRITERION	3
TESTS OF SIGNIFICANCE	7
CONCLUSIONS	14
BIBLIOGRAPHY	15

INTRODUCTION

Consider a randomized block design with p treatments occurring on each of b blocks. If each of the first n_1 treatments have variance σ_1^2 and each of the next n_2 treatments have variance σ_2^2 , etc., and

$\sum_{i=1}^K n_i = p$, the mathematical model is:

$$(1.1) \quad \begin{aligned} Y_{ijk} &= \mu + t_{ij} + b_k + e_{ijk} \\ i &= 1, 2, \dots, K \\ j &= 1, 2, \dots, n_i \\ k &= 1, 2, \dots, b \end{aligned}$$

where the e_{ijk} 's are assumed to be normally distributed such that

$$\begin{aligned} E e_{ijk} &= 0 \text{ for all } i, j, \text{ and } k, \\ E e_{ijk}^2 &= \sigma_i^2 \text{ for all } j \text{ and } k, \text{ and} \\ E e_{ijk} e_{rmn} &= 0 \text{ unless } i = r, j = m, \text{ and } k = n. \end{aligned}$$

When $n_i = 1$ for all i the model is $Y_{ik} = \mu + t_i + b_k + e_{ik}$ with the same assumptions as in (1.1). Graybill (2)¹ has discussed the problem of testing $t_1 = t_2 = \dots = t_p$ when $n_i = 1$ for all i . This method involves inversion of a matrix of order $p - 1$ in the numerical analysis and is valid only if $b > p - 1$. The purpose of this paper is to give a criterion for testing $t_{11} = t_{12} = \dots = t_{Kn_K}$

¹Single numbers in parentheses refer to references in bibliography.

for the model in (1.1) where $n_i > 1$ for at least one i . If $n_i > 1$ for at least one i , the restriction $b > p - 1$ can be relaxed somewhat. It is necessary only that $b > K - 1$. The numerical analysis will involve inversion of a matrix of order $K - 1$.

TEST CRITERION

Consider the i - th subset of observations Y_{ijk} , where
 $k = 1, 2, \dots, b, j = 1, 2, \dots, n_i$. Using these observations, conduct an analysis of variance as below for each subset that $n_i > 1$.

A. O. V. for i - th Subset

Due to	d. f.	Sum of Squares	
Blocks	$b - 1$	$n_i \sum_k (y_{i.k} - y_{i..})^2$	$= A$
Treatments	$n_i - 1$	$b \sum_j (y_{ij.} - y_{i..})^2$	$= B$
Error	$(b - 1)(n_i - 1)$	$\sum_{jk} (Y_{ijk} - y_{i.k} - y_{ij.} + y_{i..})^2$	$= C$

The ratio $\frac{B}{n_i - 1} / \frac{C}{(b - 1)(n_i - 1)} = F_i$ (where $y_{ij.}$ indicates summation over k and $y_{i.k}$ indicates the average when summed over k , etc.) is distributed as Snedecor's F with d. f. $(n_i - 1)$ and $(b - 1)(n_i - 1)$ if and only if $t_{i1} = t_{i2} = \dots = t_{in_i}$. We will have $q - 1$ such analyses, each yielding an F , where $q - 1$ is the number of subsets that $n_i > 1$.

Since Y_{ijk} is a normal variate and since $E(y_{ij.} - E y_{ij.}) \cdot (y_{rj.} - E y_{rj.}) = 0$ for $r \neq i$, $y_{rj.}$ and $y_{ij.}$ are independent. Therefore $b \sum_j (y_{ij.} - y_{i..})^2$ is independent of $b \sum_j (y_{rj.} - y_{r..})^2$.

Similarly $\sum_{jk} (y_{ijk} - y_{i.k} - y_{ij.} + y_{i..})^2$ is independent of

$\sum_{jk} (y_{rjk} - y_{r.k} - y_{rj.} + y_{r..})^2$. We have, therefore, $q - 1$ indepen-

dent ratios, each distributed as Snedecor's F if and only if

$t_{i1} = t_{i2} = \dots = t_{in_i}$ for all i .

If we average our observations within each subset over each block we have:

$$(2.1) \quad \sum_{j=1}^{n_i} y_{ijk} / n_i = \mu + \sum_{j=1}^{n_i} t_{ij} / n_i + b_k + \sum_{j=1}^{n_i} e_{ijk} / n_i.$$

Denote (2.1) by B_{ik} and let $T_i = \sum_{j=1}^{n_i} t_{ij} / n_i$ and $d_{ik} = \sum_{j=1}^{n_i} e_{ijk} / n_i$.

$$\text{Then (2.2)} \quad B_{ik} = \mu + T_i + b_k + d_{ik}$$

From the assumptions in (1.1)

$$E d_{ij} = E \sum_{j=1}^{n_i} \frac{e_{ijk}}{n_i},$$

$$E d_{ij} = 0,$$

$$E d_{ij}^2 = \frac{\sigma_e^2}{n_i},$$

$$E (d_{ij} d_{is}) = 0 \text{ for } j \neq s;$$

$$E (d_{ij} d_{rj}) = 0 \text{ for } i \neq r.$$

Thus (2.2) is the model considered by Graybill and we can use

Hotelling's T^2 to test the hypothesis $H_0 : T_1 = T_2 = \dots = T_K$.

Let $x_{ij} = B_{ij} - B_{Kj}$. Consider X_j a $K \times 1$ column vector with elements

$$x_{ij}. \quad \bar{X} = \sum_j X_j / b. \quad \text{Then } \frac{(b - K + 1) b \bar{X}'}{K - 1} \left(\sum_{j=1}^b [X_j - \bar{X}] [X_j - \bar{X}]' \right)^{-1} \bar{X}$$

which we shall call F^* has Snedecor's F distribution under H_0 with $K - 1$ and $b - K + 1$ degrees of freedom (if $b > K - 1$).

Theorem I. $t_{11} = t_{12} = \dots = t_{1n_1} = t_{21} = \dots = t_{Kn_K}$ if and only if $T_1 = T_2 = \dots = T_K$ and $t_{i1} = t_{i2} = \dots = t_{in_i}$ for all i ; $i = 1, 2, \dots, K$.

Proof: 1. If $t_{i1} = t_{i2} = \dots = t_{in_i}$, $T_i = t_{i1} = t_{i2} = \dots = t_{in_i}$. If $T_1 = T_2 = \dots = T_K$, then $t_{11} = t_{12} = \dots = t_{1n_1} = t_{21} = \dots = t_{Kn_K}$. 2. If $t_{11} = t_{12} = \dots = t_{1n_1} = t_{21} = \dots = t_{Kn_K}$, then $t_{i1} = t_{i2} = \dots = t_{in_i}$ for all i and $T_1 = T_2 = \dots = T_K$.

Theorem II. B_{mn} is independent of F_i for all i .

Proof: Let $(y_{ij.} - y_{i..}) = u_{ij}$ and $(y_{ijk} - y_{i.k} - y_{ij.} + y_{i..}) = v_{ijk}$.

$$\text{Cov}(B_{mn}, u_{ij}) = 0 \text{ for } m \neq i.$$

Let us consider the case when $m = i$.

$$\begin{aligned} \text{Cov}(B_{in}, u_{ij}) &= E(e_{i.n})(e_{ij.} - e_{i..}), \\ &= E \frac{e_{ijn}^2}{bn_i} - E \sum_j \frac{e_{ijn}^2}{bn_i^2}, \\ &= \frac{\sigma_i^2}{bn_i} - \frac{\sigma_i^2}{bn_i}, \\ &= 0. \end{aligned}$$

Also $\text{Cov}(B_{mn}, v_{ijk}) = 0$ for $m \neq i$.

Let us consider the case when $m = i$.

$$\begin{aligned}
\text{Cov}(B_{in}, v_{ijk}) &= E(e_{i..n})(e_{ijk} - e_{ij.} - e_{i.k} + e_{i..}) , \\
&= E \frac{e_{ijk}^2}{n_i} - E \frac{e_{ijk}^2}{bn_i} - E \frac{\sum_j e_{ijk}^2}{n_i^2} + E \frac{\sum_j e_{ijk}^2}{bn_i^2} , \\
&= \frac{\sigma_i^2}{n_i} - \frac{\sigma_i^2}{bn_i} - \frac{\sigma_i^2}{n_i} + \frac{\sigma_i^2}{bn_i} ; \\
&= 0.
\end{aligned}$$

Since B_{mn} , u_{ij} , and v_{ijk} are normal variates and since $\text{Cov}(B_{mn}, u_{ij}) = 0$ and $\text{Cov}(B_{mn}, v_{ijk}) = 0$, B_{mn} is independent of u_{ij} and v_{ijk} . Further B_{mn} is independent of any function of u_{ij} and v_{ijk} ; hence B_{mn} is independent of F_i for all i .

Since F^* is a function of B_{ij} , F^* is independent of each of the $(q - 1)$ F 's which we obtained as in the analysis of variance on page 3. We have, therefore, q independent F 's, which are simultaneously distributed as Snedecor's F if and only if H_0 is true: i.e. if and only if $t_{11} = t_{12} = \dots = t_{1n_1} = t_{21} = \dots = t_{Kn_K}$. To test H_0 requires that we combine q independent tests of significance.

TESTS OF SIGNIFICANCE

1. Product of Beta Variables (4)

The product of beta variables with parameters (a_1, b_1) , (a_2, b_2) , . . . (a_q, b_q) such that $a_i = (a_i + 1 + b_i + 1)$ is distributed as a beta variable with parameters $(a_q, b_1 + \dots + b_q)$. Since the transformation $w = m F/n / (1 + mF/n)$ transforms $F(m, n)$ to a beta variable with parameters $\alpha = m/2$, $\beta = n/2$, in some cases we may be able to transform each F_i and F^* to beta variables, form the product, and use Pearson's tables of the incomplete beta function to test H_0 .

2. Pearson's P_λ Test

If P_1, P_2, \dots, P_q are q independent probabilities then $-2 \log_e P_i$ is distributed as χ^2 [2]. P_λ is therefore distributed as χ^2 [2q].

3. Wilkinson's Methods

Reject H_0 if and only if $P_i \leq \alpha$ for r or more of the P_i 's where r is a predetermined integer, $1 \leq r \leq q$, and α is a constant corresponding to the desired confidence level. The q possible choices of r give q different procedures (case 1, case 2, etc.). Birnbaum (1) indicates that, while there is no single case best for all problems, case 1 seems to be best for this type of problem.

4. Case 1 of Wilkinson's Method

Reject H_0 if and only if at least one $F_i > h_i$ where

$P(F_i > h_i \mid H_0) = \alpha$ for all i ; α is predetermined by the desired type

I error, i.e. $P(I)$. $P(\text{of rejecting } H_0 \mid \text{given } H_0 \text{ is true})$ equals

$$\sum_{i=1}^q P(F_i > h_i) - \sum_{ij} P(F_i > h_i) P(F_j > h_j) +$$

$$\sum_{ijk} P(F_i > h_i) P(F_j > h_j) P(F_k > h_k) - \dots + P(F_1 > h_1) P(F_2 > h_2) \cdot$$

$\dots P(F_q > h_q)$ where the second sum is over all combinations of the

numbers $1, 2, \dots, q$ taken two at a time, the third is over combina-

tions of the numbers three at a time, etc. Hence $P(I) = 1 - (1 - \alpha)^q$.

For any desired $P(I)$ we can determine α .

The power of the test $\beta = P(\text{reject } H_0 \mid H_1)$ equals

$$1 - \prod_{i=1}^q P(F_i < h_i \mid H_1).$$

5. Comparison of Graybill's Method with the Method Proposed in this Paper.

Let us denote the method proposed in this paper by A and the method proposed by Graybill by B. A comparison of the powers will be made only for case 1 of Wilkinson's methods. For this comparison let us consider the original model (1.1) :

$$Y_{ijk} = \mu + t_{ij} + b_k + e_{ijk}$$

for $i = 1, 2, \dots, n_1$, $j = 1, 2, \dots, n_2$, and $k = 1, 2, \dots, b$.

Method A will be considered first. Using the nb observations Y_{ijk} form the ratio of mean square for treatments to mean square for error. This ratio is distributed as Snedecor's F with $n - 1$ and $(n - 1)(b - 1)$ d. f. when $t_{11} = t_{12} = \dots = t_{1n}$.

Consider the means:

$$y_{i.k} = \mu + t_{i.} + b_k + e_{i.k}$$

$$i = 1, 2$$

$$k = 1, 2, \dots, b.$$

To test the hypothesis $t_{1.} = t_{2.}$ we use the ratio of the mean square for

treatments, $\sum_{ik} (y_{i.k} - y_{...})^2$, to the mean square for error

$$\sum_{ik} (y_{i.k} - y_{i..} - y_{..k} + y_{...})^2 / (b - 1). \text{ This ratio is distributed}$$

as Snedecor's F with 1 and $b - 1$ d. f. when $t_{1.} = t_{2.}$

The power of the test, β_A , using method A equals

$$1 - P(F_1 < h_1 \mid H_1) P(F_2 < h_2 \mid H_1).$$

We can evaluate β_A by transforming F_1 and F_2 to Tang's E^2 . Making

the transformation $z_1 = f_{11}F_1 / (f_{12} + f_{11}F_1)$, where f_{11} and f_{12} are the degrees of freedom for F_1 , we have z_1 distributed as

Tang's E^2 with parameters $n - 1$, $(n - 1)(b - 1)$, and λ_1 where

$$\lambda_1 = b \sum_j (t_{1j} - t_{1.})^2 / 2\sigma_1^2. \text{ Also } z_2 \text{ is distributed as Tang's } E^2$$

with parameters 1, $b - 1$, and λ_2 where $\lambda_2 = \frac{bm(t_{1.} - t_{21})^2}{2(\sigma_1^2 + n\sigma_2^2)}.$

Hence $P(F_1 < h_1 \mid H_1) = \int_0^{g_1} f(z_1) dz_1$ and $P(F_2 < h_2 \mid H_1)$ equals

$\int_0^{g_1} f(z_2) dz_2$ where g_1 and g_2 are determined by the transformation

$g_1 = f_{i1}h_i / (f_{i2} + f_{i1}h_i)$. Therefore the power of method A equals

$$1 - \int_0^{g_1} f(z_1) dz_1 \int_0^{g_1} f(z_2) dz_2 .$$

For method B Graybill has shown that if we let

$$u_{jk} = Y_{1jk} - Y_{21k}$$

that

$$(3.1) \quad \bar{U}' \left(\sum_k [U_k - \bar{U}] [U_k - \bar{U}]' \right)^{-1} \bar{U} \frac{(b-n)b}{n} = F^*$$

where $\bar{U} = \sum_k U_k / b$ and $U_k =$

$$\begin{bmatrix} u_{k1} \\ u_{k2} \\ u_{k3} \\ \vdots \\ u_{kn} \end{bmatrix} ,$$

is distributed as Snedecor's F with b and b - p d. f. when

$$t_{11} = t_{12} = \dots t_{1n} = t_{21} .$$

Therefore

$$U_i \sim N(\mu^*, A)$$

where

$$\mu^* = \begin{bmatrix} t_{11} - t_{21} \\ t_{12} - t_{21} \\ \dots \\ t_{1n} - t_{21} \end{bmatrix} .$$

and

$$A = (a_{ij})$$

where

$$a_{ij} = \sigma_1^2 + \sigma_2^2 \quad \text{if } i = j ,$$

and

$$a_{ij} = \sigma_2^2 \quad \text{if } i \neq j .$$

Under H_1 , F^* is distributed as the non-central F with parameters

n , $b - n$, and λ_3 where $\lambda_3 = \frac{\mu^* A^{-1} \mu^*}{2}$. To find λ_3 we must examine the variance-covariance matrix A .

A is a circulant matrix and $A^{-1} = B$ is found to be (b_{ij}) where

$$b_{ij} = \frac{\sigma_1^2 + (n-1)\sigma_2^2}{\sigma_1^2(\sigma_1^2 + n\sigma_2^2)} \quad \text{if } i = j,$$

$$b_{ij} = \frac{-\sigma_2^2}{\sigma_1^2(\sigma_1^2 + n\sigma_2^2)} \quad \text{if } i \neq j.$$

Then $\lambda_3 = Cb/2$ where C is defined as below.

Writing t_{21} as t_2 , let

$$\begin{aligned} C &= \sum_{ij} (t_{1i} - t_2) b_{ij} (t_{1j} - t_2) \\ &= \sum_{ij} (t_{1j} - t_{1.} - t_2 + t_{1.}) (t_{1j} - t_{1.} - t_2 + t_{1.}) b_{ij} \\ &= \sum_{ij} (t_{1i} - t_{1.})(t_{1j} - t_{1.}) b_{ij} - 2 \sum_{ij} (t_2 - t_{1.})(t_{1i} - t_{1.}) b_{ij} \\ &\quad + (t_2 - t_{1.})^2 \sum_{ij} b_{ij} \\ &= \sum_{ij} (t_{1i} - t_{1.})(t_{1j} - t_{1.}) b_{ij} + \frac{(t_2 - t_{1.})^2}{\sigma_1^2 + n\sigma_2^2}. \end{aligned}$$

$$\text{Let } K = \sum_{ij} (t_{1j} - t_{1.})(t_{1j} - t_{1.}) b_{ij}.$$

$$K = \sum_i (t_{1i} - t_{1.})^2 b_{ii} + \sum_i \sum_{j \neq i} (t_{1j} - t_{1.})(t_{1j} - t_{1.}) b_{ij}$$

$$\begin{aligned}
&= \sum_i (t_{1i} - t_{1.})^2 \frac{(\sigma_1^2 + [n-1] \sigma_2^2)}{\sigma_1^2 (\sigma_1^2 + n\sigma_2^2)} \\
&\quad + \sum_i (t_{1i} - t_{1.}) \sum_{j \neq i} (t_{1j} - t_{1.}) \frac{(-\sigma_2^2)}{\sigma_1^2 (\sigma_1^2 + n\sigma_2^2)} \\
&= \frac{\sum_i (t_{1i} - t_{1.})^2 (\sigma_1^2 + [n-1] \sigma_2^2) + \sum_i (t_{1i} - t_{1.}) \sigma_2^2}{\sigma_1^2 (\sigma_1^2 + n\sigma_2^2)} \\
&= \sum_i (t_{1i} - t_{1.})^2 / \sigma_1^2 .
\end{aligned}$$

Therefore

$$\lambda_3 = \frac{b \sum_i (t_{1i} - t_{1.})^2}{2 \sigma_1^2} + \frac{bn (t_2 - t_{1.})^2}{2(\sigma_1^2 + n\sigma_2^2)} .$$

That is,

$$\lambda_3 = \lambda_1 + \lambda_2 .$$

Power of B = $1 - \int_0^{g_3} f(z_3) dz_3$ where z_3 is distributed as Tang's E^2 with parameters n , $b - n$, and λ_3 .

We can now compare the power of method A with the power of method B. In order to use Tang's tables we must compute ϕ_1

where

$$\phi_i = \sqrt{\frac{2\lambda_i}{f_{i1} + 1}}$$

for

$$i = 1, 2, \text{ and } 3.$$

Since $\lambda_3 = \lambda_1 + \lambda_2$, ϕ_3 is a function of ϕ_1 and ϕ_2 . For the special case where $n = 3$, $b = 5$, and $P(I) = .02$, the power of A is compared with the power of B in the table on the following page. The values for

the power of B were obtained by double interpolation from Tang's tables.

Comparison of Powers

ϕ_1	ϕ_2	A	B
1	1	0.118	0.053
1	3	0.545	0.140
1	5	0.928	0.220
3	1	0.823	0.113
3	3	0.906	0.250
3	5	0.986	0.360
5	1	0.999	0.360
5	3	0.999	0.406
5	5	1.000	0.480

These data indicate that, for small samples, method A is more powerful than method B.

CONCLUSIONS

If an exact method of combining independent tests of significance is used, the method proposed in this paper to test treatment means equal is exact. Its power seems to be better than that of the method proposed by Graybill. It should also be emphasized that the method in this paper requires inversion of a smaller matrix than Graybill's method. In addition, the restriction that b be greater than K is much less stringent than the restriction in Graybill's method that b be greater than $p - 1$.

BIBLIOGRAPHY

- (1) Birnbaum, Allen. "Combining Independent Tests of Significance." Journal of the American Statistical Association, 49 (September, 1954), 559-574.
- (2) Graybill, Franklin. "Variance Heterogeneity in a Randomized Block Design." Biometrics, 10 (December, 1954), 516-520.
- (3) Kempthorne, O. The Design and Analysis of Experiments. New York: John Wiley and Sons, 1950.
- (4) Rao, C. Radhakrishna. Advanced Statistical Methods in Biometric Research. New York: John Wiley and Sons, 1952.

VITA

John Leroy Folks
candidate for the degree of
Master of Science

Thesis: HETEROGENEITY OF ERROR VARIANCES IN A RANDOMIZED BLOCK
DESIGN

Major: Mathematics

Minor: Statistics

Biographical and Other Items:

Born: October 12, 1929 near Hydro, Oklahoma

Undergraduate Study: Southwestern State College, 1947-50;
O. A. M. C., 1952-53

Graduate Study: O. A. M. C., 1953-54; V. P. I., 1954;
O. A. M. C., 1954-55

Experiences: Army, 45th Infantry Division in Japan and Korea
1950-52; Graduate teaching assistant in Mathematics
Department 1953-54, 1954-55

Member of Pi Mu Epsilon, American Statistical Association, American
Mathematical Society, and Associate Member of The Society of
the Sigma Xi.

Date of Final Examination: May, 1955

THESIS TITLE: HETEROGENEITY OF ERROR VARIANCES
IN A RANDOMIZED BLOCK DESIGN

AUTHOR: John Leroy Folks

THESIS ADVISER: Dr. Franklin Graybill

The content and form have been checked and approved by the author and thesis adviser. The Graduate School Office assumes no responsibility for errors either in form or content. The copies are sent to the bindery just as they are approved by the author and faculty adviser.

TYPIST: Gayle Rogers