

# Implementation of a new solution to the multivariate Behrens–Fisher problem

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**Abstract.** Krishnamoorthy and Yu (2004, *Statistics and Probability Letters* 66: 161–169) published a new approximate solution to the multivariate Behrens–Fisher problem. It is a modification of Nel and Van der Merwe’s (1986, *Communications in Statistics, Theory and Methods* 15: 3719–3735) test. The test is invariant and identical to Welch’s test for one-dimensional data. In this article, I describe an implementation of the test in Stata. The `hotelmm` command allows you to perform the test easily and returns computed values for possible further computations.

**Editors’ note:** The `mvtest means` command introduced in Stata 11 produces the same test as the `hotelmm` command introduced here. Use the `heterogenous` option of `mvtest means` to obtain the test; see [MV] `mvtest means`. The `hotelmm` command will still be of interest to those using prior versions of Stata.

**Keywords:** st0180, hotelmm, multivariate Behrens–Fisher problem, Nel and Van der Merwe’s test, Welch’s test

## 1 Introduction

In its univariate form, the Behrens–Fisher problem is the test of the difference between the means of two normally distributed populations when the variances of the populations are not necessarily equal. Because an exact analytic solution is computationally intractable, different approximate solutions are used. The most popular is Welch’s test. This test is provided in Stata through `ttest` using the `unequal` option.

Multivariate generalization of the  $t$  test, testing the equality of two vector means, is Hotelling’s test. As in the univariate case, Hotelling’s test assumes that the variance matrices of the two groups are equal. Stata provides the `hotelling` procedure for this case. In this article, I provide a modification of `hotelling`, called `hotelmm`, that can be used when the variance–covariance matrices of the group-specific outcome means may be unequal.

Let’s introduce some notation. We assume two independent  $p$ -variate random samples from normal distributions

$$X_1, \dots, X_m \sim \mathcal{N}_p(\mu_1, \Sigma_1)$$

and

$$Y_1, \dots, Y_n \sim \mathcal{N}_p(\mu_2, \Sigma_2)$$

Thus every  $X_i$  and  $Y_j$  is a vector of length  $p$  (there are  $p$  different characteristics measured on one object). Mean values of the two populations are  $\mu_1$  and  $\mu_2$ , and their variance matrices are  $\Sigma_1$  and  $\Sigma_2$ . Sample sizes  $m$  and  $n$  may be different. We want to test the null hypothesis  $H_0 : \mu_1 = \mu_2$  against  $H_a : \mu_1 \neq \mu_2$  when  $\Sigma_1 \neq \Sigma_2$ .

Test of this hypothesis is called the multivariate Behrens–Fisher problem.

The situation in a general  $p$ -variate case is more complicated than in the univariate one. First, we have to realize that  $H_0$  is equivalent to

$$H_A : A\mu_1 = A\mu_2$$

for any nonsingular matrix  $A$ . That is why it is reasonable to request that the test of  $H_0$  should be independent of any data transformation by a nonsingular matrix  $A$ . This property, if present, is called the invariance of the test. The exact solution is again known but computationally intractable (see [Nel, Van der Merwe, and Moser \[1990\]](#)). Other published solutions include the following:

- Solution of [Scheffé \(1943\)](#) and [Bennett \(1950\)](#): uses adjusted paired differences. It is an exact solution but has little power because it does not use the information from the samples well. It is analogical to using a paired  $t$  test in place of a two-sample  $t$  test.
- Approximate solutions:
  - [Kim \(1992\)](#), [Nel and Van der Merwe \(1986\)](#): not invariant.
  - [James \(1954\)](#), [Yao \(1965\)](#), [Johansen \(1980\)](#): varying quality of the approximation. James' solution is not used any more. It is difficult to predict which one of the latter two will be better in a specific situation.

As a result, none of the solutions is commonly accepted. A new solution appeared recently: [Krishnamoorthy and Yu \(2004\)](#). It is a modified version of [Nel and Van der Merwe's \(1986\)](#) test. The merit of the authors is especially in the derivation of the correct number of degrees of freedom, when they noticed incorrectness in [Nel and Van der Merwe's](#) derivation. This solution is invariant, and it seems to have a stable test level close to the chosen  $\alpha$ . It coincides with Welch's test for  $p = 1$ . In my opinion, it has a big chance to become the most popular solution of the problem.

## 2 The principle

Notice that for  $\Sigma_1 = \Sigma_2$ , we can write Hotelling's test statistic in the following way:

$$T^2 = (\bar{X} - \bar{Y})' \left( \frac{1}{m}S + \frac{1}{n}S \right)^{-1} (\bar{X} - \bar{Y})$$

where  $S$  is the pooled variance matrix estimator.

Let's denote

$$S_1 = \frac{1}{m-1} \sum_{i=1}^m (X_i - \bar{X}) (X_i - \bar{X})' \quad \text{and} \quad S_2 = \frac{1}{n-1} \sum_{i=1}^n (Y_i - \bar{Y}) (Y_i - \bar{Y})'$$

both sample variance matrices, and

$$\Sigma = \frac{1}{m} \Sigma_1 + \frac{1}{n} \Sigma_2 \quad \text{and} \quad S = \frac{1}{m} S_1 + \frac{1}{n} S_2$$

For  $\Sigma_1 \neq \Sigma_2$  it is natural to define

$$T^2 = (\bar{X} - \bar{Y})' \left( \frac{1}{m} S_1 + \frac{1}{n} S_2 \right)^{-1} (\bar{X} - \bar{Y})$$

This test statistic has approximately Hotelling's distribution, as it is shown in Krishnamoorthy and Yu (2004). The corresponding number of degrees of freedom is

$$f^* = \frac{\text{Tr}(I_p^2) + (\text{Tr} I_p)^2}{\frac{1}{m-1} \left\{ \text{Tr}(V_1^2) + (\text{Tr} V_1)^2 \right\} + \frac{1}{n-1} \left\{ \text{Tr}(V_2^2) + (\text{Tr} V_2)^2 \right\}}$$

where

$$V_1 = \Sigma^{-\frac{1}{2}} \frac{1}{m} \Sigma_1 \Sigma^{-\frac{1}{2}} \quad \text{and} \quad V_2 = \Sigma^{-\frac{1}{2}} \frac{1}{n} \Sigma_2 \Sigma^{-\frac{1}{2}}$$

Reasonable estimators of  $V_1$  and  $V_2$  are

$$\hat{V}_1 = S^{-\frac{1}{2}} \frac{1}{m} S_1 S^{-\frac{1}{2}} \quad \text{and} \quad \hat{V}_2 = S^{-\frac{1}{2}} \frac{1}{n} S_2 S^{-\frac{1}{2}}$$

As a consequence, a reasonable estimator of  $f^*$  is

$$d = \frac{p(p+1)}{\frac{1}{m^2(m-1)} \left\{ \text{Tr}(S_1 S^{-1})^2 + (\text{Tr} S_1 S^{-1})^2 \right\} + \frac{1}{n^2(n-1)} \left\{ \text{Tr}(S_2 S^{-1})^2 + (\text{Tr} S_2 S^{-1})^2 \right\}}$$

or

$$\begin{aligned} \frac{1}{d} = \frac{1}{p(p+1)} & \left[ \frac{1}{m^2(m-1)} \left\{ \text{Tr}(S_1 S^{-1})^2 + (\text{Tr} S_1 S^{-1})^2 \right\} + \right. \\ & \left. + \frac{1}{n^2(n-1)} \left\{ \text{Tr}(S_2 S^{-1})^2 + (\text{Tr} S_2 S^{-1})^2 \right\} \right] \end{aligned}$$

Thus

$$T^2 \stackrel{H_0}{\approx} T_{d,p}^2$$

or

$$\frac{d-p+1}{dp} T^2 \stackrel{H_0}{\approx} F_{p,d-p+1}$$

It is easy to see that for  $p = 1$ ,  $d$  is equal to Welch’s number of approximate degrees of freedom. Moreover, Krishnamoorthy and Yu (2004) showed that even for  $p > 1$ ,  $d$  is bound in the same way as in the one-dimensional case:

$$\min(m - 1, n - 1) \leq d \leq m + n - 2$$

$d$  being close to the upper bound tells us that the two variance matrices are (almost) equal. The closer  $d$  is to the lower bound, the bigger the discrepancy is between them. The lower bound is attained only if one of  $S_1, S_2$  is a zero matrix.

### 3 The hotelmnm command

#### 3.1 Syntax

The syntax of the `hotelmnm` command is

```
hotelmnm varlist [if] [in] , by(groupvar) [notable]
```

The `if` or `in` condition can restrict input data (observations).

#### 3.2 Options

`by(groupvar)` is required. It specifies the name of the grouping variable. *groupvar* must contain exactly two different values.

`notable` suppresses the table of basic descriptive statistics in the output.

#### 3.3 Saved results

`hotelmnm` saves the following in `r()`:

##### Scalars

<code>r(k)</code>	number of variables
<code>r(N1)</code>	number of observations in the first group
<code>r(N2)</code>	number of observations in the second group
<code>r(df)</code>	number of approximate degrees of freedom
<code>r(T2)</code>	value of $T^2$ statistic

##### Matrices

<code>r(X)</code>	averages of both groups
<code>r(S1)</code>	sample variance matrix of the first group
<code>r(S2)</code>	sample variance matrix of the second group

All these values can be used for further computations.

## 4 Example 1

```
. sysuse auto
(1978 Automobile Data)
. hotelmnm mpg headroom, by(foreign)
```

---

```
-> foreign = Domestic
```

Variable	Obs	Mean	Std. Dev.	Min	Max
mpg	52	19.82692	4.743297	12	34
headroom	52	3.153846	.9157578	1.5	5

---

```
-> foreign = Foreign
```

Variable	Obs	Mean	Std. Dev.	Min	Max
mpg	22	24.77273	6.611187	14	41
headroom	22	2.613636	.4862837	1.5	3.5

2-group approximate Hotelling's T-squared with unequal variances = 18.402703  
F test statistic:  $((44.102882-2+1)/(44.102882)(2)) \times 18.402703 = 8.9927177$   
H0: Vectors of means are equal for the two groups  
 $F(2,43.102882) = 8.9927$   
 $\text{Prob}(F > F(2,43.102882)) = 0.000544$

## 5 Example 2

```
. hotelmnm mpg headroom trunk if price<5000, by(foreign) notable
```

2-group approximate Hotelling's T-squared with unequal variances = 13.209688  
F test statistic:  $((12.765519-3+1)/(12.765519)(3)) \times 13.209688 = 3.7133664$   
H0: Vectors of means are equal for the two groups  
 $F(3,10.765519) = 3.7134$   
 $\text{Prob}(F > F(3,10.765519)) = 0.046656$

```
. display " n1 = " r(N1) ", n2 = " r(N2) ", dimension = " r(k)
n1 = 29, n2 = 8, dimension = 3
. display " degrees of freedom = " r(df) ", T^2 = " r(T2)
degrees of freedom = 12.765519, T^2 = 13.209688
. matrix list r(X)
r(X) [2,3]
```

	mpg	headroom	trunk
group1	22.137931	3.0689655	12.517241
group2	28.875	2.75	10.625

```
. matrix list r(S1)
symmetric r(S1) [3,3]
```

	mpg	headroom	trunk
mpg	19.051724		
headroom	-2.2777094	.94150246	
trunk	-7.8953202	2.945197	13.544335

```
. matrix list r(S2)
symmetric r(S2) [3,3]
```

	mpg	headroom	trunk
mpg	23.839286		
headroom	-.60714286	.21428571	
trunk	-9.9107143	.39285714	12.839286

## 6 References

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### About the author

Ivan Žežula is a statistician at Šafárik University in Košice, Slovakia. He is involved in many applications of statistics, especially in medicine. He considers Stata to be a handy tool for both teaching and research, and he occasionally writes his own procedures.