

# How can I get Type III tests of fixed effects in R?

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June 30, 2024

## RECOMMENDED CITATION

stats writer (2024). *How can I get Type III tests of fixed effects in R?*. PSYCHOLOGICAL SCALES. Retrieved from <https://scales.arabpsychology.com/?p=161814>

Type III tests of fixed effects in R are statistical procedures used to determine the significance of individual fixed effects in a linear mixed effects model. This type of analysis is particularly useful in situations where there are multiple fixed effects and the researcher is interested in understanding the unique contribution of each one. To obtain Type III tests of fixed effects in R, one can use the "Anova" function from the "car" package or the "lmerTest" package. These functions allow for the calculation of Type III sums of squares, which can then be used to test the significance of each fixed effect. Additionally, the "lmerTest" package also provides options for obtaining p-values and confidence intervals for the fixed effects. Overall, using Type III tests of fixed effects in R can provide valuable insights into the individual effects of predictors in a linear mixed effects model.

## How can I get Type III tests of fixed effects in R? | R FAQ

When running a mixed-effects model with categorical predictors, you may wish to test the fixed effects of the model. When your model includes categorical variables with three or more levels or interactions, this requires a multiple degrees of freedom test. In other software packages like SAS, Type III tests of fixed effects are presented with the regression output. In R, this is not the case. However, we can use contrast and ANOVA-type commands to extract these effects.

We will use the dataset `hsbdemo` and the R packages `foreign` (to

read in the data) and nlme (to run a mixed-effects model). We will run a random-intercept model where read is predicted by female, prog, and math.

```
library(foreign)
library(nlme)
```

```
d1 <- read.dta("https://stats.idre.ucla.edu/stat/data/hsbdemo.dta")
attach(d1)
```

In order to use contrast commands, we will need to convert our string factor variables to integer factor variables starting at 1.

```
female12 <- as.factor(1*(female=="male") +
2*(female=="female"))
```

```
prog123 <- as.factor(1*(prog=="general") +
2*(prog=="academic") + 3*(prog=="vocational"))
```

Next, before running the model, we define the contrasts for our factor variables.

For a simple model without interactions, we can use the `contr.treatment` command which also allows us to specify a baseline (which is helpful if you are attempting to match model results seen in a publication or another software). We provide the number of levels and the level we wish to use as the baseline. This command generates a corresponding matrix that we then indicate as the contrast matrix for a given variable using the `contrasts` command. These matrices correspond to "dummy coding" the categorical variables. For further information on dummy coding, see [FAQ: What is dummy coding?](#).

```
a <- contr.treatment(2, base = 2, contrasts = TRUE)
class(a)
"matrix"
```

```
a
1
```

```
1 1
```

```
2 0
```

```
b <- contr.treatment(3, base = 3, contrasts = TRUE)
```

```
b
```

```
1 2
```

```
1 1 0
```

```
2 0 1
```

```
3 0 0
```

```
contrasts(female12) <- a
```

```
contrasts(prog123) <- b
```

We can now run our model and see that the coefficients of the model are reported according to the baselines indicated in these contrasts.

```
m1.lme <- lme(read ~ female12 + prog123 + math,  
random =~ 1|cid, method = "ML")  
summary(m1.lme)
```

**Linear mixed-effects model fit by maximum likelihood**

**Data: NULL**

**AIC BIC logLik**

**1289.254 1312.342 -637.6271**

**Random effects:**

**Formula: ~1 | cid**

**(Intercept) Residual**

**StdDev: 11.00646 4.809769**

**Fixed effects: read ~ female12 + prog123 + math**

**Value Std.Error DF t-value p-value**

**(Intercept) 70.08683 4.776200 176 14.674184 0.0000**

**female121 1.35292 0.731138 176 1.850427 0.0659**

**prog1231 -2.10673 1.006942 176 -2.092208 0.0379**

**prog1232 -2.04756 0.968723 176 -2.113675 0.0360**

**math -0.33022 0.074898 176 -4.408968 0.0000**

**Correlation:**

**(Intr) fml121 pr1231 pr1232**

**female121 -0.035**

**prog1231 -0.231 -0.022**

**prog1232 -0.223 -0.001 0.415**

**math -0.843 -0.039 0.195 0.188**

**Standardized Within-Group Residuals:**

**Min Q1 Med Q3 Max**

**-2.5019691 -0.6206737 0.0354358 0.7148373 2.3331462**

**Number of Observations: 200**

**Number of Groups: 20**

To see the Type III tests of fixed effects, we use the `anova.lme`

command. To indicate Type III tests, we provide `type = "marginal"`.

```
anova.lme(m1.lme, type = "marginal", adjustSigma = F)
```

```
numDF denDF F-value p-value  
(Intercept) 1 176 220.85299 <.0001  
female12 1 176 3.51188 0.0626  
prog123 2 176 3.20534 0.0429  
math 1 176 19.93743 <.0001
```

If we have a more complex model that includes interactions of categorical variables, dummy coding no longer captures the main effects of these categorical variables but rather the simple effects. To test for main effects in our Type III tests, we will need to use a different contrast command that defines our

**categorical variables using "effect coding". The contrast matrices under effect coding are no longer composed of only zeroes and ones; each column in the contrast matrix now sums to zero. We can create these effect coding matrices in R with the `contr.sum` function.**

```
contrasts(female12) <- contr.sum  
contrasts(female12)
```

```
1 1  
2 -1
```

```
contrasts(prog123) <- contr.sum  
contrasts(prog123)
```

```
0 1 0  
1 0 1  
2 -1 -1
```

**For more information on effect coding, see [FAQ: What is effect coding?](#). We can run our model to estimate coefficients based on this coding,**

then generate the desired tests after running the model.

```
m1.lme2 <- lme(read ~ female12*prog123 + math,
random =~ 1|cid, method = "ML")
summary(m1.lme2)
```

Linear mixed-effects model fit by maximum likelihood

Data: NULL

AIC BIC logLik

1288.429 1318.114 -635.2145

Random effects:

Formula: ~1 | cid

(Intercept) Residual

StdDev: 10.88791 4.751459

Fixed effects: read ~ female12 \* prog123 + math

Value Std.Error DF t-value p-value

(Intercept) 68.77214 4.674240 174 14.713011 0.0000

female121 0.94010 0.386053 174 2.435143 0.0159

prog1231 -0.69864 0.613890 174 -1.138046 0.2567

prog1232 -0.62045 0.590308 174 -1.051065 0.2947

math -0.31881 0.075398 174 -4.228375 0.0000

female121:prog1231 -0.02636 0.566363 174 -0.046538

0.9629

female121:prog1232 0.98816 0.584777 174 1.689812  
0.0929

### Correlation:

(Intr) fml121 pr1231 pr1232 math f121:1231

female121 0.035

prog1231 -0.064 0.001

prog1232 -0.076 0.009 -0.581

math -0.844 -0.033 0.093 0.110

female121:prog1231 0.129 0.123 0.137 -0.097 -0.149

female121:prog1232 -0.127 0.163 -0.072 0.086 0.148  
-0.644

### Standardized Within-Group Residuals:

Min Q1 Med Q3 Max

-2.40201967 -0.66416223 0.05083885 0.71444086  
2.32978676

anova.lme(m1.lme2, type = "marginal", adjustSigma = F)

numDF denDF F-value p-value

(Intercept) 1 174 224.32402 <.0001

female12 1 174 6.14499 0.0141

prog123 2 174 2.96372 0.0542

math 1 174 18.52762 <.0001

female12:prog123 2 174 2.44197 0.0900

**The table output from the `anova.lme` command contains the Type III tests of fixed effects for this model.**

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