Something to Remember About Factorial ANOVA using SPSS GLM

GLM provides both "traditional ANOVA output" and "regression output" for the same analysis.

Here's an example, using the relationship between Gender and depression.

Descriptive Statistics

Dependent Variable: DEP

GENDER	Mean	Std. Deviation	N
male	5.3432	5.91411	169
female	7.8402	7.12801	194
Total	6.6777	6.69899	363

Tests of Between-Subjects Effects

Dependent Variable: DEP

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	563.148[a]	1	563.148	12.964	.000
Intercept	15697.727	1	15697.727	361.359	.000
GENDER	563.148	1	563.148	12.964	.000
Error	15682.141	361	43.441		
Total	32432.000	363			
Corrected Total	16245.289	362			

a. R Squared = .035 (Adjusted R Squared = .032)

Parameter Estimates

Dependent Variable: DEP

Parameter	B	Std. Error	t	Sig.
Intercept	7.840	.473	16.568	.000
[GENDER=1]	-2.497	.694	-3.600	.000
[GENDER=2]	0[a]	.	.	.

a. This parameter is set to zero because it is redundant.

For the regression parameter estimates SPSS computes a dun code for the fixed factor, using the largest coded group (here female) as the comparison group.

Notice that, as expected, the b weight matches the mean difference – male mean is 2.497 larger than the female mean.

Also, the F the effect of gender is t^2 for the gender parameter.

Also, the results are the same as if we computed a dummy code with females as the comparison group ourselves and then used regression to perform the analysis.

if (gender = 1) genc = 1.
if (gender = 2) genc = 0.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.186[a]	.035	.032	6.59097

a. Predictors: (Constant), GENC

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	7.840	.473		16.568	.000
	GENC	-2.497	.694	-.186	-3.600	.000

a. Dependent Variable: DEP

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	563.148	1	563.148	12.964	.000[a]
	Residual	15682.141	361	43.441		
	Total	16245.289	362			

a. Predictors: (Constant), GENC

b. Dependent Variable: DEP

We get the same thing all 3 ways …

Same df, SS & F

Same effect size

Same b

Same $F = t^2$

However, watch what happens when we switch to a factorial design – here with the fixed effects of gender and marital status and the outcome variable depression.

Descriptive Statistics

Dependent Variable: DEP

GENDER	MARITAL	Mean	Std. Deviation	N
male	single	5.0492	5.58459	122
	married	6.1064	6.69923	47
	Total	5.3432	5.91411	169
female	single	9.0417	8.10995	120
	married	5.8919	4.57081	74
	Total	7.8402	7.12801	194
Total	single	7.0289	7.22053	242
	married	5.9752	5.47032	121
	Total	6.6777	6.69899	363

Parameter Estimates

Dependent Variable: DEP

Parameter	B	Std. Error	t	Sig.
Intercept	5.892	.756	7.792	.000
[GENDER=1]	.214	1.213	.177	.860
[GENDER=2]	0[a]	.	.	.
[MARITAL=1]	3.150	.961	3.276	.001
[MARITAL=2]	0[a]	.	.	.
[GENDER=1] * [MARITAL=1]	-4.207	1.474	-2.855	.005
[GENDER=1] * [MARITAL=2]	0[a]	.	.	.
[GENDER=2] * [MARITAL=1]	0[a]	.	.	.
[GENDER=2] * [MARITAL=2]	0[a]	.	.	.

a. This parameter is set to zero because it is redundant.

Tests of Between-Subjects Effects

Dependent Variable: DEP

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1055.189[a]	3	351.730	8.313	.000
Intercept	13262.668	1	13262.668	313.447	.000
GENDER	278.122	1	278.122	6.573	.011
MARITAL	85.324	1	85.324	2.017	.156
GENDER * MARITAL	344.868	1	344.868	8.151	.005
Error	15190.100	359	42.312		
Total	32432.000	363			
Corrected Total	16245.289	362			

a. R Squared = .065 (Adjusted R Squared = .057)

YIKES!

Neither the gender main effect, nor the marital main effect match for the ANOVA and parameter estimates -- F ? t^2 and the b values don't reflect the marginal mean differences!

However, the interaction does match -- $2.855^2 = 8.151$, and the interaction b (-4.207) reflects the difference between the simple effect of marital for males (-1.0562) and for females (3.1498) → 4.207.

Why does this happen? The confluence of two things…

The ANOVA summary table reflects the use of "effects coding" (the highest coded group for each IV is the comparison group and is weighted -1 and the interaction term is the product of the two main effect codes), whereas the parameter estimates reflect the use of dummy coding (the highest coded group for each IV is the comparison group and is weighted 0 and the interaction term is the product of the two main effect codes),

Effect codes and dummy codes are not linear transformations of each other, and so using them leads to different patterns of colinearity between the main effects terms of the model, and so, different expressions of the main effects.

Two things to notice:

1. The interaction term is the same for both effect coded and dummy coded versions. This may be why some folks suggest ignoring main effects if you have an interaction – because the interaction term is the same for various coding schemes. However, even if you delete a non-contributing interaction term, the main effects will still appear different for a dummy and effect coded analysis.

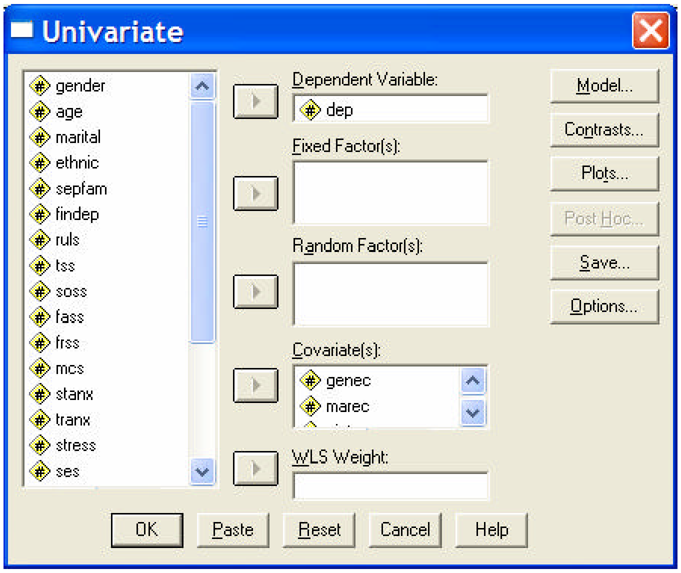
2. This effect won't show up if there is =n for the factorial design. If so, the main effects are orthogonal and so there's no colinearity to be partitioned differently by the different coding schemes. Some folks base upon this the suggestion that factorial analyses should be reserved for =n designs. Others counter that this is an artificial simplification of the patterns of "real colinearity" among variables. These folks suggest that differences between the main effects results using dummy vs. effect coding is no more "troublesome" than the differences between the main effects results when using alternative operational differences (manipulation or measurement) of the IVs. In either case you select your "preferred" operationalization and judiciously interpret the results.

One nice thing about GLM is that you can include any variable, of any type, using the covariate window. So, to show you that the above result is a coding thing, here's the result of making effects codes for the main effects and the interaction and then including these directly into the GLM.

```
if (gender = 1) genec = 1.
if (gender = 2) genec = -1.

if (marital = 1) marec = 1.
if (marital = 2) marec = -1.

compute eint = genec *
marec.
```



Using effect codes produces parameter estimates that match the ANOVA summary table.

The regression weights don't reflect the main effect marginal mean differences, because the parameters "correct for" the colinearity amongst the effects.

This will be important when doing factorial ANCOVAs, because the corrections of effects for the covariate will depend upon the expression of the main effects (as dummy codes or effects codes) because which we use will influence the colinearity among the main effects and with the covariates.

Tests of Between-Subjects Effects

Dependent Variable: DEP

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1055.189[a]	3	351.730	8.313	.000
Intercept	13262.668	1	13262.668	313.45	.000
GENEC	278.122	1	278.122	6.573	.011
MAREC	85.324	1	85.324	2.017	.156
EINT	344.868	1	344.868	8.151	.005
Error	15190.100	359	42.312		
Total	32432.000	363			
Corrected Total	16245.289	362			

a. R Squared = .065 (Adjusted R Squared = .057)

Parameter Estimates

Dependent Variable: DEP

Parameter	B	Std. Error	t	Sig.
Intercept	6.522	.368	17.704	.000
GENEC	-.944	.368	-2.564	.011
MAREC	.523	.368	1.420	.156
EINT	-1.052	.368	-2.855	.005