

Descriptive Statistics

```
. summarize age attend happy married male racenew sexfreq
```

Variable	Obs	Mean	Std. Dev.	Min	Max
age	2751	46.28281	17.37049	18	89
attend	2743	3.662413	2.70204	0	8
happy	1369	1.821037	.6289519	1	3
married	2765	.4589512	.4984023	0	1
male	2765	.444123	.4969578	0	1
racenew	2762	.7585083	.4280652	0	1
sexfreq	2151	2.825198	2.013244	0	6

“Obs” = The number of observations with valid responses for each variable. For general happiness there are 1369 valid responses.

“Minimum” = The minimum possible value for each variable. Recall that values for general happiness are coded (1) very happy, (2) pretty happy, and (3) not too happy.

“Maximum” = The maximum possible value for each variable.

“Mean” = The mean value for all 2751 cases. Respondents have a mean age of 46.28 years.

“Std. Deviation” = The standard deviation is a measure of dispersion around the mean. For example, the mean age for this sample is 46, with a standard deviation of 17. So, 95% of the cases in a normal distribution will be between 29 and 63.

Since we have coded race, gender, and marital status as a dummies, the mean can be interpreted as the percent of respondents reporting the focus category (1=white, 1=male, 1=married). For gender, 44% of the respondents are male. For race, 76% of the respondents are White. For marital status, 46% of the respondents are married.

Frequencies

In this example, we compare the “table” and “tabulate” commands in STATA. We recoded the missing values to “-9” so that it could be shown in the tables.

```
. table happy
```

general happiness	Freq.
-9	1,396
very happy	415
pretty happy	784
not too happy	170

The “freq.” column indicates simply the number of cases in each of the categories. In this example, 415 of the cases have a value of (1) very happy and 1396 of the cases have missing values (-9).

```
. tabulate happy
```

general happiness	Freq.	Percent	Cum.
-9	1,396	50.49	50.49
very happy	415	15.01	65.50
pretty happy	784	28.35	93.85
not too happy	170	6.15	100.00
Total	2,765	100.00	

The “tabulate” command provides “freq.,” “percent,” and the cumulative percent (“cum.”). In this example, 415 of the cases (15.01%) have a value of (1) very happy and 1396 (50.49%) of the cases have missing values (-9).

Correlations

The correlation tells you the magnitude and direction of the association between two variables.

```
. pwcorr happy sexfreq age , obs sig
```

	happy	sexfreq	age
happy	1.0000 1369		
sexfreq	-0.1053 0.0006 1060	1.0000 2151	
age	-0.0453 0.0944 1362	-0.4370 0.0000 2143	1.0000 2751

Here is the correlation between age of respondent and frequency of sex. The correlation coefficient is $-.437$ (and is significant). This suggests a negative correlation with moderate magnitude. As age increases, the frequency of sex decreases. The correlation between age and frequency of sex is $-.437$. If we square this value, we get $.190969$, or 19.1 out of 100, or 19.1 percent. From this we can claim that 19.1% of the correlation in frequency of sex is attributed to respondent's age.

This cell represents the correlation (and significance and sample size) between age and general happiness. The top value ($-.045$) is the correlation coefficient. The middle value ($.094$) is the significance. The bottom value (1362) is the number of cases. In this example, the correlation is not significant, at the $p < .05$ level.

Note

The following general categories indicate a quick way of interpreting correlations.

- 0.0 – 0.2 Very weak correlation
- 0.2 – 0.4 Weak correlation
- 0.4 – 0.7 Moderate correlation
- 0.7 – 0.9 Strong correlation
- 0.9 – 1.0 Very strong correlation

T-Test

The Independent Sample T-Test compares the mean scores of two groups on a given variable. In this example, we compare “frequency of sex” for males versus females.

Null Hypothesis: The means of the two groups (males and females) are not significantly different.
 Alternate Hypothesis: The means of the two groups (males and females) are significantly different.

```
. oneway sexfreq sex
```

Source	SS	df	MS	F	Prob > F
Between groups	134.322319	1	134.322319	33.64	0.0000
Within groups	8579.95197	2149	3.99253233		
Total	8714.27429	2150	4.05315083		

```
Bartlett's test for equal variances:  chi2(1) = 6.3875  Prob>chi2 = 0.011
```

Bartlett’s test tests the hypothesis that our samples have equal variances. If the Chi-Square test is significant ($p < .05$), then we can reject the null hypothesis and assume that variances are unequal. In this case, Chi-Square is significant and we can reject the null hypothesis and assume that variances are unequal.

ANNOTATED OUTPUT--STATA

```
. ttest sexfreq , by(sex)
```

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
male	976	3.099385	.0612103	1.912271	2.979266	3.219504
female	1175	2.597447	.0602927	2.06673	2.479153	2.71574
combined	2151	2.825198	.0434086	2.013244	2.74007	2.910325
diff		.5019384	.0865368		.3322339	.6716429

Degrees of freedom: 2149

Ho: mean(male) - mean(female) = diff = 0

Ha: diff < 0
t = 5.8003
P < t = 1.0000

Ha: diff != 0
t = 5.8003
P > |t| = 0.0000

Ha: diff > 0
t = 5.8003
P > t = 0.0000

We can see here that males report higher frequencies of sex than females. However, we cannot tell from here whether or not this difference is significant.

Our "t" value is 5.842. There is a significant difference between the two groups. We can conclude, then, that males and females significantly differ in their reports of sexual frequency: males reported higher levels of sexual frequency than did females. The circled value indicates the difference in means (male score minus female score).

Crosstab (with Chi-Square)

A crosstabulation displays the number of cases in each category defined by two or more grouping variables.

The Chi Square Goodness of Fit test determines if the observed frequencies are different from what we would expect to find (we expect equal numbers in each group within a variable).

Null Hypothesis: There are approximately equal numbers of cases in each group.

Alternate Hypothesis: There are not equal numbers of cases in each group.

```
. tabulate happy freqdum , chi2
```

general happiness	sexfreq dummy		Total
	less than	more than	
very happy	103	207	310
pretty happy	286	333	619
not too happy	63	68	131
Total	452	608	1,060

For example, we see that there are 207 cases reporting “very happy” for general happiness and “more than once per month” for frequency of sex.

Pearson chi2(2) = 16.0387 Pr = 0.000

The Chi-Square measure tests the hypothesis that the row and column variables in a crosstabulation are independent of one another. While the Chi-Square measure may indicate that there is a relationship between two variables, they do not indicate the strength or direction of the relationship.

ANOVA

The One-Way ANOVA compares the mean of one or more groups based on one independent variables (or factor). We assume that the dependent variable is normally distributed and that groups have approximately equal variance on the dependent variable.

Null Hypothesis: There are no significant differences between groups' mean scores.

Alternate Hypothesis: There is a significant difference between groups' mean scores.

In this example, we compare “frequency of sex” by church attendance, recoded from 9 groups to 3 groups (0=not often, 1=sometimes, 2=often).

```
. anova sexfreq church
```

```
Number of obs = 2142      R-squared      = 0.0132
Root MSE      = 2.00297   Adj R-squared = 0.0122
```

Source	Partial SS	df	MS	F	Prob > F
Model	114.423493	2	57.2117464	14.26	0.0000
church	114.423493	2	57.2117464	14.26	0.0000
Residual	8581.45139	2139	4.01189873		
Total	8695.87488	2141	4.06159499		

$$F = \frac{\text{variance between groups}}{\text{variance expected due to chance (error)}} = \frac{57.212}{4.012} = 14.26$$

If the sample means are clustered closely together (i.e., small differences), the variance will be small; if the means are spread out (i.e., large differences), the variances will be larger.

Our F value is 14.261. Our significance level is .000. We can conclude that there is a significant difference between the three groups. To determine which groups are different from one another, we use the “multiple comparisons” results below.

Simple Linear Regression

Simple Linear Regression tells you the amount of variance accounted for by one variable in predicting another variable.

```
. reg sexfreq age marital racenew happy attend
```

Source	SS ^c	df	MS			
Model ^a	1382.66217	5	276.532435	Number of obs =	1052	
Residual ^b	2850.06406	1046	2.72472664	F(5, 1046) =	101.49 ^d	
				Prob > F =	0.0000	
				R-squared =	0.3267 ^e	
				Adj R-squared =	0.3234	
Total	4232.72624	1051	4.02733229	Root MSE =	1.6507 ^f	

sexfreq	Coef.	Std. Err.	t ^g	P> t	[95% Conf. Interval]	
age	-.0554982	.0030401	-18.26	0.000	-.0614636	-.0495327
marital	-1.372326	.1071273	-12.81	0.000	-1.582535	-1.162117
racenew	-.2153774	.1252702	-1.72	0.086	-.4611869	.0304321
happy	-.2618401	.084642	-3.09	0.002	-.4279275	-.0957527
attend	-.0674279	.0196243	-3.44	0.001	-.1059354	-.0289204
_cons	8.298	.2966264	27.97	0.000	7.715949	8.88005

- a.** The output for Model displays information about the variation accounted for by the model.
- b.** The output for Residual displays information about the variation that is not accounted for by your model. And the output for Total is the sum of the information for Regression and Residual.
- c.** A model with a large model sum of squares in comparison to the residual sum of squares indicates that the model accounts for most of variation in the dependent variable. Very high residual sum of squares indicate that the model fails to explain a lot of the variation in the dependent variable, and you may want to look for additional factors that help account for a higher proportion of the variation in the dependent variable. In this example, we see that 32.5% of the total sum of squares is made up from the regression sum of squares. You may notice that the R^2 for this model is also .325 (this is not a coincidence!).
- d.** If the significance value of the F statistic is small (smaller than say 0.05) then the independent variables do a good job explaining the variation in the dependent variable. If the significance value of F is larger than say 0.05 then the independent variables do not explain the variation in the dependent variable. For this example, the model does a good job explaining the variation in the dependent variable.

ANNOTATED OUTPUT--STATA

- e.** The “R Square” tells us how much of the variance of the dependent variable can be explained by the independent variable(s). In this example, 32.7% of the variance in frequency of sex is explained by differences in all included variables.
- f.** The standard error of the estimate (aka, the root mean square error), is the standard deviation of the error term, and is the square root of the Mean Square Residual (or Error).
- g.** The t statistics can help you determine the relative importance of each variable in the model. The t-statistic is calculated by divided the variable’s unstandardized coefficient by its standard error. As a guide regarding useful predictors, look for t values well below -1.96 or above +1.96. As you can see, the race variable is the only t-value not within this range (note also that this is the only variable that is not significant).

Regression Equation

$$\text{SEXFREQ}_{\text{predicted}} = 8.298 - .055*\text{age} - 1.372*\text{marital} - .215*\text{race} - .262*\text{happy} - .067*\text{attend}$$

If we plug in values in for the independent variables (age = 35 years; marital = currently married-1; race = white-1; happiness = very happy-1; church attendance = never attends-0), we can predict a value for frequency of sex:

$$\begin{aligned}\text{SEXFREQ}_{\text{predicted}} &= 8.298 - .055*35 - 1.372*1 - .215*1 - .262*1 - .067*0 \\ &= 4.524\end{aligned}$$

As this variable is coded, a 35-year old, White, married person with high levels of happiness and who never attends church would be expected to report their frequency of sex between values 4 (weekly) and 5 (2-3 times per week).

If we plug in 70 years, instead, we find that frequency of sex is predicted at 2.599, or approximately 1-2 times per month.

Model Interpretation

Constant = The predicted value of “frequency of sex”, when all other variables are 0. In this example, a value of 8.298 is not interpretable, since the valid responses for frequency of sex range from 0-6. Important to note, values of 0 for all variables is not interpretable either (i.e., age cannot equal 0).

Age = For every unit increase in age (in this case, year), frequency of sex will decrease by .055 units.

Marital Status = For every unit increase in marital status, frequency of sex will decrease by 1.372 units. Since marital status has only two categories, we can conclude that currently married persons have more sex than currently unmarried persons.

Race = For every unit increase in race, frequency of sex will decrease by .215 units. For example, the difference between non-White (0) to White (1) would be .215 units.

Happiness = For every unit increase in happiness, frequency of sex will decrease by .262 units. Recall that happiness is coded such that higher scores indicate less happiness. For this example, then, higher levels of happiness predict higher frequency of sex.

Church Attendance = For every unit increase in church attendance, frequency of sex decreases by .067 units.

Simple Linear Regression (with Age-Squared Variable)

It is known that some variables are often non-linear, or curvilinear. Such variables may be age or income. In this example, we include the original age variable and an age squared variable.

```
. reg sexfreq age marital racenew happy attend agesquar
```

Source	SS	df	MS			
Model	1394.24116	6	232.373526	Number of obs =	1052	
Residual	2838.48508	1045	2.71625366	F(6, 1045) =	85.55	
Total	4232.72624	1051	4.02733229	Prob > F =	0.0000	
				R-squared =	0.3294	
				Adj R-squared =	0.3255	
				Root MSE =	1.6481	

sexfreq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
age	-.0204952	.0172229	-1.19	0.234	-.0542906	.0133002
marital	-1.31425	.1105973	-11.88	0.000	-1.531268	-1.097232
racenew	-.2183136	.1250833	-1.75	0.081	-.4637567	.0271295
happy	-.2713968	.0846369	-3.21	0.001	-.4374745	-.1053191
attend	-.0670664	.0195946	-3.42	0.001	-.1055156	-.0286172
agesquar	-.0003523	.0001706	-2.06	0.039	-.0006872	-.0000175
_cons	7.466803	.4997854	14.94	0.000	6.486106	8.4475

The age squared variable is significant, indicating that age is non-linear.

Simple Linear Regression (with interaction term)

In a linear model, the effect of each independent variable is always the same. However, it could be that the effect of one variable depends on another. In this example, we might expect that the effect of age is dependent on sex. In the following example, we include an interaction term, age*sex.

To test for two-way interactions (often thought of as a relationship between an independent variable (IV) and dependent variable (DV), moderated by a third variable), first run a regression analysis, including both independent variables (IV and moderator) and their interaction (product) term. It is highly recommended that the independent variable and moderator are standardized before calculation of the product term, although this is not essential. The product term should be significant in the regression equation in order for the interaction to be interpretable.

For this example, two dummy variables were created, for ease of interpretation. Sex was recoded such that 1=Male and 0=Female. Marital status was recoded such that 1=Currently married and 0=Not currently married. The interaction term is a cross-product of these two dummy variables.

Regression Model (without interactions)

```
. reg sexfreq age racenew happy attend male married
```

Source	SS	df	MS			
Model	1419.69041	6	236.615068	Number of obs =	1052	
Residual	2813.03583	1045	2.69190031	F(6, 1045) =	87.90	
Total	4232.72624	1051	4.02733229	Prob > F =	0.0000	
				R-squared =	0.3354	
				Adj R-squared =	0.3316	
				Root MSE =	1.6407	

sexfreq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
age	-.0547746	.003028	-18.09	0.000	-.0607164	-.0488329
racenew	-.2307659	.1245824	-1.85	0.064	-.4752261	.0136942
happy	-.2421688	.0842976	-2.87	0.004	-.4075806	-.076757
attend	-.0562567	.0197369	-2.85	0.004	-.0949852	-.0175281
male	.3852511	.103874	3.71	0.000	.1814257	.5890764
married	1.317949	.1074847	12.26	0.000	1.107038	1.528859
_cons	5.295466	.2582801	20.50	0.000	4.788659	5.802273

ANNOTATED OUTPUT--STATA

Regression Model (*with interactions*)

```
. reg sexfreq age racenew happy attend male married interact
```

Source	SS	df	MS	Number of obs =	1052
Model	1444.99234	7	206.427478	F(7, 1044) =	77.31
Residual	2787.73389	1044	2.67024319	Prob > F =	0.0000
Total	4232.72624	1051	4.02733229	R-squared =	0.3414
				Adj R-squared =	0.3370
				Root MSE =	1.6341

sexfreq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
age	-.0532626	.0030556	-17.43	0.000	-.0592584 - .0472668
racenew	-.2625718	.1245097	-2.11	0.035	-.5068896 - .0182541
happy	-.2508243	.0840049	-2.99	0.003	-.4156619 - .0859866
attend	-.0525717	.0196938	-2.67	0.008	-.0912157 - .0139278
male	.6725887	.1393423	4.83	0.000	.3991658 .9460117
married	1.630128	.147462	11.05	0.000	1.340772 1.919484
interact	-.6434146	.2090208	-3.08	0.002	-1.053563 -.2332659
_cons	5.135983	.2624047	19.57	0.000	4.621082 5.650883

Regression Equation

$$\text{SEXFREQ}_{\text{predicted}} = 5.136 - .053 * \text{age} - .263 * \text{race} - .251 * \text{happy} - .053 * \text{attend} + 1.630 * \text{married} + (.673 - .643 * \text{married}) * \text{male}$$

Interpretation

Main Effects

The married coefficient represents the main effect for females (the 0 category). The effect for females is then 1.63, or the “marital” coefficient. The effect for males is 1.63 - .643, or .987.

The gender coefficient represents the main effect for unmarried persons (the 0 category). The effect for unmarried is then .673, or the “sex” coefficient. The effect for married is .673 - .643, or .03.

Interaction Effects

For a simple interpretation of the interaction term, plug values into the regression equation above.

$$\begin{aligned}
 \text{Married Men} &= \text{SEXFREQ}_{\text{predicted}} = 5.136 - .053*35 - .263*1 - .251*1 - .053*0 + 1.630*1 + (.673 - .643*1) * 1 &= 5.455 \\
 \text{Married Women} &= \text{SEXFREQ}_{\text{predicted}} = 5.136 - .053*35 - .263*1 - .251*1 - .053*0 + 1.630*1 + (.673 - .643*1) * 0 &= 5.425 \\
 \text{Unmarried Men} &= \text{SEXFREQ}_{\text{predicted}} = 5.136 - .053*35 - .263*1 - .251*1 - .053*0 + 1.630*0 + (.673 - .643*0) * 1 &= 3.825 \\
 \text{Unmarried Women} &= \text{SEXFREQ}_{\text{predicted}} = 5.136 - .053*35 - .263*1 - .251*1 - .053*0 + 1.630*0 + (.673 - .643*0) * 0 &= 3.795
 \end{aligned}$$

In this example (age = 35 years; race = white-1; happiness = very happy-1; church attendance = never attends-0), we can see that (1) for both married and unmarried persons, males are reporting higher frequency of sex than females, and (2) married persons report higher frequency of sex than unmarried persons. The interaction tells us that the gender difference is greater for married persons than for unmarried persons.

Logistic Regression

Logistic regression is a variation of the regression model. It is used when the dependent response variable is binary in nature. Logistic regression predicts the probability of the dependent response, rather than the value of the response (as in simple linear regression).

In this example, the dependent variable is frequency of sex (less than once per month versus more than once per month).

```
. logistic freqdum age marital racenew attend happy
```

```
Logistic regression                Number of obs   =       1052
                                   LR chi2(5)        =       302.11
                                   Prob > chi2       =       0.0000
Log likelihood = -567.40591         Pseudo R2     =       0.2102b
```

freqdum	Odds Ratio ^a	Std. Err.	z	P> z	[95% Conf. Interval]	
age	.9408818	.0047102	-12.17	0.000	.9316952	.950159
marital	.17496	.0290688	-10.49	0.000	.1263327	.2423048
racenew	.8854209	.1564181	-0.69	0.491	.626292	1.251765
attend	.9309624	.0262984	-2.53	0.011	.8808194	.9839599
happy	.7156043	.087177	-2.75	0.006	.5636079	.9085918

a. The “Odds Ratio” is the predicted change in odds for a unit increase in the predictor. When the Odds Ratio is less than 1, increasing values of the variable correspond to decreasing odds of the event's occurrence. When the Odds Ratio is greater than 1, increasing values of the variable correspond to increasing odds of the event's occurrence.

If you subtract 1 from the odds ratio and multiply by 100, you get the percent change in odds of the dependent variable having a value of 1. For example, for age:

$$= 1 - (.941) = .059$$

$$= .059 * 100 = 5.9\%$$

The odds ratio for age indicates that every unit increase in age is associated with a 5.9% decrease in the odds of having sex more than once a month.

b. The R-Square statistic cannot be exactly computed for logistic regression models, so these approximations are computed instead. Larger pseudo r-square statistics indicate that more of the variation is explained by the model, to a maximum of 1.

Interpretation

Recall: When $\text{Exp}(B)$ is less than 1, increasing values of the variable correspond to decreasing odds of the event's occurrence. When $\text{Exp}(B)$ is greater than 1, increasing values of the variable correspond to increasing odds of the event's occurrence.

Constant = Not interpretable in logistic regression.

Age = Increasing values of age correspond with decreasing odds of having sex more than once a month.

Marital = Increasing values of marital status (married to unmarried) correspond with decreasing odds of having sex more than once a month.

Race = Increasing values of race correspond with increasing odds of having sex more than once a month. Notice that this variable, however, is not significant.

Church Attendance = Increasing values of church attendance correspond with decreasing odds of having sex more than once a month.

Happiness = Increasing values of general happiness correspond with decreasing odds of having sex more than once a month. Recall that happiness is coded such that higher values indicate less happiness.

Logistic Regression (with non-linear variables)

It is known that some variables are often non-linear, or curvilinear. Such variables may be age or income. In this example, we include the original age variable and an age squared variable.

```
. logistic freqdum age marital racenew attend happy agesquar
```

```
Logistic regression                Number of obs   =       1052
                                   LR chi2(6)        =       314.11
                                   Prob > chi2       =       0.0000
Log likelihood = -561.40465         Pseudo R2     =       0.2186
```

freqdum	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]
age	1.029322	.0274165	1.09	0.278	.9769654 1.084485
marital	.1876667	.0319891	-9.82	0.000	.1343674 .2621081
racenew	.8854594	.1559968	-0.69	0.490	.6269129 1.250633
attend	.9311651	.0264615	-2.51	0.012	.8807195 .9845002
happy	.7026621	.085654	-2.89	0.004	.5533319 .8922928
agesquar	.9990557	.0002795	-3.38	0.001	.998508 .9996037

The age squared variable is significant, indicating that age is non-linear.

Logistic Regression (with interaction term)

To test for two-way interactions (often thought of as a relationship between an independent variable (IV) and dependent variable (DV), moderated by a third variable), first run a regression analysis, including both independent variables (IV and moderator) and their interaction (product) term. It is highly recommended that the independent variable and moderator are standardized before calculation of the product term, although this is not essential. For this example, two dummy variables were created, for ease of interpretation. Sex was recoded such that 1=Male and 0=Female. Marital status was recoded such that 1=Currently married and 0=Not currently married. The interaction term is a product of these two dummy variables.

Regression Model (without interactions)

```
. logistic freqdum age racenew happy attend male married
```

```
Logistic regression                Number of obs   =      1052
                                   LR chi2(6)       =      311.10
                                   Prob > chi2      =      0.0000
Log likelihood = -562.91057        Pseudo R2      =      0.2165
```

freqdum	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]
age	.9407224	.0047616	-12.07	0.000	.9314359 .9501014
racenew	.8615719	.1535544	-0.84	0.403	.6075547 1.221793
happy	.7273111	.0893135	-2.59	0.010	.5717327 .9252252
attend	.9422746	.0269726	-2.08	0.038	.8908649 .996651
male	1.558383	.2310822	2.99	0.003	1.165347 2.083978
married	5.464756	.9139101	10.16	0.000	3.937479 7.584435

ANNOTATED OUTPUT--STATA

Regression Model (with interactions)

```
. logistic freqdum age racenew happy attend male married interact
```

```
Logistic regression                Number of obs   =       1052
                                   LR chi2(7)        =       313.87
                                   Prob > chi2       =       0.0000
Log likelihood = -561.5232          Pseudo R2     =       0.2184
```

freqdum	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]
age	.9417151	.0047935	-11.80	0.000	.9323667 .9511572
racenew	.8412302	.1508375	-0.96	0.335	.591956 1.195474
happy	.7244743	.0892968	-2.61	0.009	.5689921 .9224436
attend	.9452654	.0271617	-1.96	0.050	.8935009 1.000029
male	1.913216	.3698852	3.36	0.001	1.309784 2.794655
married	6.93103	1.542039	8.70	0.000	4.481461 10.71953
interact	.6043344	.1827447	-1.67	0.096	.3341046 1.093131

The product term should be significant in the regression equation in order for the interaction to be interpretable. In this example, the interaction term is significant at the 0.1 level.

Interpretation

Main Effects

The married coefficient represents the main effect for females (the 0 category). The effect for females is then 1.94, or the “marital” coefficient. The effect for males is 1.94 - .50, or 1.44.

The gender coefficient represents the main effect for unmarried persons (the 0 category). The effect for unmarried is then .65, or the “sex” coefficient. The effect for married is .65 - .50, or .15.

Odds Ratios

Using “married” as the focus variable, we can say that the effect of being married on having sex more than once per month is greater for females.

Females: $e^{1.936} = 6.93$

Males: $e^{1.432} = 4.20$

Using “gender” as the focus variable, we can say that the effect of being male on having sex more than once per month is greater for marrieds.

Marrieds: $e^{0.15} = 1.16$

Unmarrieds: $e^{0.65} = 1.92$