Dale Berger
Claremont Graduate University

Hierarchical Regression Demonstration

Gender Differences in Psychology Faculty Salaries

This example demonstrates hierarchical mediation regression analysis and a bit of data cleaning. Important lesson: If different analyses give different results, we have asked different questions.

These are real data from the APA Research Office, taken from a 2005 study of salaries of faculty in graduate psychology programs. The original data file included only five variables: gender, rank (lecturer through full professor), level of program where the faculty member is employed (M.A. vs. PhD), salary, and years in rank.

Questions: Is there a gender difference in salary? Do we have evidence of sex discrimination? The quick boilerplate analysis is an independent groups t-test.

Click Analyze, Compare Means, Independent Samples T-Test… Select **salary** as the Test Variable and **Sex** as the Grouping Variable. Define the levels for Sex. (**1, 2**). Click Paste and run the syntax.

```
T-TEST
  GROUPS = sex(1 2)
  /MISSING = ANALYSIS
  /VARIABLES = salary
  /CRITERIA = CI(.95) .
```

Group Statistics

	sex gender	N	Mean	Std. Deviation	Std. Error Mean
salary 9-10-month salary	1 Men	2803	77,188.02	27,061.030	511.132
	2 Women	1839	67,442.49	23,376.364	545.112

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
salary 9-10-month salary	Equal variances assumed	54.008	.000	12.654	4640	.000	9,745.528	770.173
	Equal variances not assumed			13.042	4306.9	.000	9,745.528	747.264

This shows the average salary for men to be \$77,188.02 and the average salary for women to be \$67,442.49, a difference of \$9745.53 favoring men. The standard t-test is $t = 12.65$, $df = 4640$, $p < .001$. A hasty conclusion is that female faculty members are paid 87 cents for every dollar a male faculty member is paid for comparable work (\$67,442 / \$77,188 = .87).

What additional factors might account for variability in salaries? We know that people with greater seniority generally are paid more. Perhaps faculty who teach in PhD programs are paid more than those who teach in MA programs. We have information on these variables so we can test to what extent these variables along with sex account for variance in individual salaries.
We should begin by examining our data and preparing the data for regression analysis. We will begin by looking at the data. A good place to begin is with frequencies and histograms for each of our variables. We will ask for the mean, SD, skew, kurtosis, minimum, and maximum for each of the five variables.

Statistics

		sex gender	rank academic rank	level Degree level	salary 9-10-month salary	rankyrs years in rank
N	Valid	4642	4642	4642	4642	4642
	Missing	0	0	0	0	0
Mean		1.40	1.86	1.17	73,327.18	6.87
Std. Deviation		.489	.867	.377	26,101.056	4.059
Skewness		.425	.440	1.748	1.594	-.188
Std. Error of Skewness		.036	.036	.036	.036	.036
Kurtosis		-1.820	-1.125	1.055	3.658	-1.346
Std. Error of Kurtosis		.072	.072	.072	.072	.072
Minimum		1	1	1	22,317	1
Maximum		2	4	2	261,375	14

We note that kurtosis = 3.658 for our criterion variable (salary) and the maximum value of $261,375 is quite extreme. If the distribution of salary was normal with a mean of $73,327 and a standard deviation of $26,101, the maximum value of 261,375 would correspond to a z-score of (261,375 – 73,327) / 26,101 = 11.68! We have a large data set so probably our analyses will not be very sensitive to an outlier of this magnitude, but we may wish to do some sensitivity analyses to make sure. Possibly a log transformation of salary will produce a distribution that is much closer to normal in shape.

Sex and Level are coded (1,2). Interpretability in regression is improved if we use dummy coding (0,1) instead.

sex gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 Men	2803	60.4	60.4	60.4
	2 Women	1839	39.6	39.6	100.0
	Total	4642	100.0	100.0	

There are more men than women faculty in our sample, but that is not a problem for our analyses.

rank academic rank

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 Full professor	2032	43.8	43.8	43.8
	2 Associate professor	1311	28.2	28.2	72.0
	3 Assistant professor	1215	26.2	26.2	98.2
	4 Lecturer/Instructor	84	1.8	1.8	100.0
	Total	4642	100.0	100.0	

There are only 84 faculty in the lecturer category. Typically these are non-tenure track positions. We may wish to limit our analyses to tenure track positions.

level Degree level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 Doctoral-level department	3848	82.9	82.9	82.9
	2 Master's-level department	794	17.1	17.1	100.0
	Total	4642	100.0	100.0	

Only 17% of the faculty teach in Master's level departments. Again, this does not pose a problem for our analyses – the sample is large even for this smaller group. We can examine the extent to which faculty gender varies with this variable.

rankyrs years in rank

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 12 or more years	1044	22.5	22.5	22.5
	4 6-11 years	467	10.1	10.1	32.6
	5 3-5 years	278	6.0	6.0	38.5
	6 Less than 3 years	243	5.2	5.2	43.8
	7 6 or more years	601	12.9	12.9	56.7
	9 3-5 years	302	6.5	6.5	63.2
	10 Less than 3 years	408	8.8	8.8	72.0
	11 3 or more years	594	12.8	12.8	84.8
	12 Less than 3 years	621	13.4	13.4	98.2
	13 3 or more years	47	1.0	1.0	99.2
	14 Less than 3 years	37	.8	.8	100.0
	Total	4642	100.0	100.0	

The table shows interesting peculiarities in the coding of this important variable. I asked SPSS to show both the values and the labels (Edit, Options, Output labels…). Although the maximum value is 14, there are only 11 categories because there are no cases with values equal to 2, 3, or 8. Smaller numbers reflect MORE time in rank (opposite to intuitive coding). The values of 13 and 14 show 84 cases, apparently the lecturers. We could run a crosstab between **rankyrs** and **rank** (I did) to verify that the **rankyrs** = 1 refers to Full Professors who were in rank 12+ years while 14 refers to lecturers who were in that rank for less than 3 years, etc.

rankyrs needs to be recoded for regression analysis. It generally is best to code variables so that larger values indicate more of the quantity referred to in the label and so steps are of equal size at all levels of the variable. First, we will code **rankyrs** into a new variable called **rankcode** where 1=Lecturer less than 3 years and 11=Full Professor 12 or more years. Note that the intervals are not equal in years. For additional analyses, we will create a new variable that is an estimate of the number of years in tenure track positions, omitting Lecturers (**yearstt**). We also will compute the log of salary to reduce the impact of positive skew and a few especially large salaries (**lnsal**).

We know that Assistant Professors typically are in that rank no more than six years, so an Assistant Professor who is '3 or more years' in rank is estimated to be in rank 3, 4, 5, or 6 years (an average of 4.5 years). Full Professors in rank '12 or more years' are estimated to be faculty members for 25 years. The impact of these estimates can be assessed with sensitivity analyses. For example, we could replace 25 with 30 to see how the analyses are affected.

Here is syntax that accomplishes the desired recodes:

```
recode sex (1=0)(2=1) into sexd.
recode level (1=1)(2=0) into leveld.
RECODE   rankyrs (1=11)(4=10)(5=9)(6=8)(7=7)(9=6)(10=5)(11=4)(12=3)(13=2)(14=1) into rankcode.
Recode rankcode (3=1.5)(4=4.5)(5=7.5)(6=10)(7=13)(8=13)(9=15)(10=19.5)(11=25)(else=sysmis) into
yearstt.
Compute lnsal = ln(salary).
Variable labels
  rankcode 'Academic ranks in order'
 /yearstt 'Estimated years in tenure track'
 /lnsal = log of salary.
Value labels
 sexd 0 'Male' 1 'Female'
/leveld 0 'MA' 1 'PhD'
/rankcode 1 'Lect<3' 2 'Lect3+' 3 'Asnt<3' 4 'Asnt3+'  5 'Assoc<3' 6 'Assoc3-5'   7 'Assoc6+'  8
'Full<3' 9 'Full3-5' 10 'Full6-11' 11 Full12+' .
```

Now, let's conduct a regression analysis comparing men and women on salary.

Click Analyze, Regression, Linear…, select **salary** as the Dependent and **sexd** as the Independent, click Paste and run the syntax.

Descriptive Statistics

	Mean	Std. Deviation	N
salary 9-10-month salary	73,327.18	26,101.056	4642
sexd sexd (M=0;F=1)	.40	.489	4642

The overall mean salary is $73,327.18, and the sample has 40% female faculty.

Correlations

		salary 9-10-month salary	sexd sexd (M=0;F=1)
Pearson Correlation	salary 9-10-month salary	1.000	-.183
	sexd sexd (M=0;F=1)	-.183	1.000
Sig. (1-tailed)	salary 9-10-month salary	.	.000
	sexd sexd (M=0;F=1)	.000	.
N	salary 9-10-month salary	4642	4642
	sexd sexd (M=0;F=1)	4642	4642

The negative correlation indicates that people higher on the Sex variable are lower on salary; i.e., females are paid less.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.183[a]	.033	.033	25,664.807

a. Predictors: (Constant), sexd sexd (M=0;F=1)

b. Dependent Variable: salary 9-10-month salary

Caution: R is always reported as positive.
Sex predicts 3.3% of the variance in salary.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	77188.018	484.760		159.23	.000
	sexd sexd (M=0;F=1)	-9745.528	770.173	-.183	-12.654	.000

a. Dependent Variable: salary 9-10-month salary

The constant is the predicted value for a case where all predictors are equal to zero. In this model, the value on **sexd** is zero for males, so the modeled mean salary for males is $77,188.02. For females, **sexd** = 1, so we multiply the B for **sexd** by 1 to find that modeled salary for females is $9,745.53 less. Compare these values to the means and other results from the initial t-test.

Now let's limit the analysis to faculty in tenure track positions, those with **rankcode** > 2.
Click Data, Select cases…, select If, click If, enter **rankcode > 2**.
Now rerun the regression analysis.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	77620.087	486.138		159.667	.000
	sexd sexd (M=0;F=1)	-9540.099	775.747	-.179	-12.298	.000

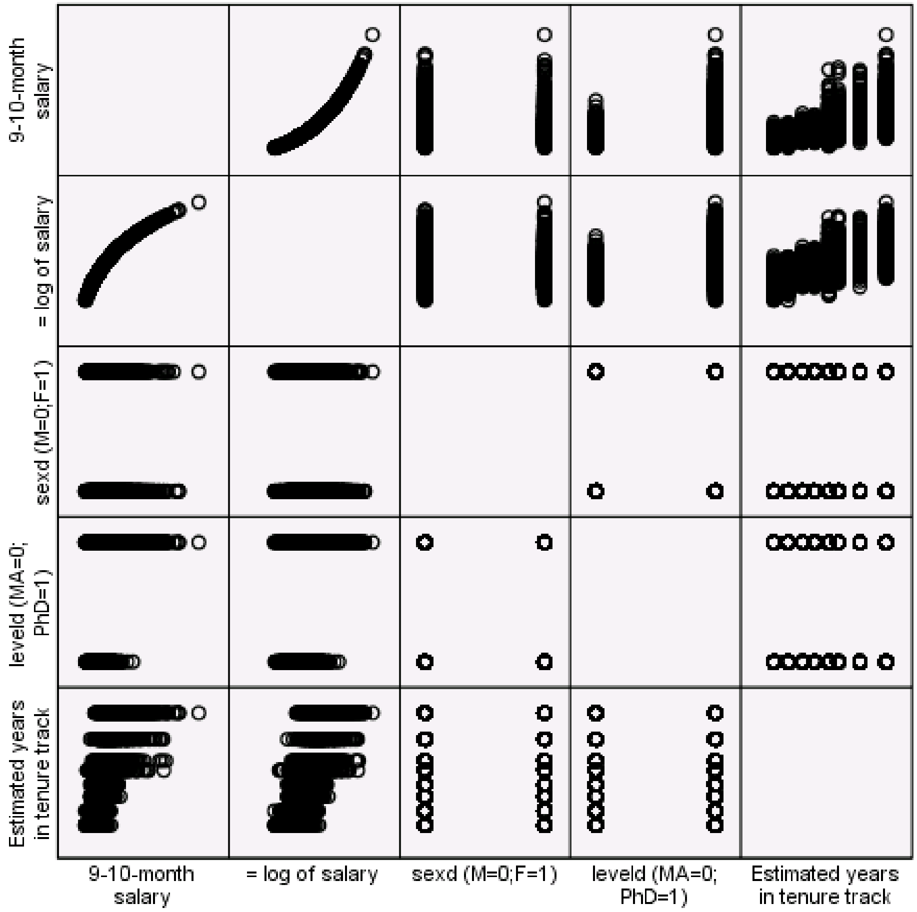
a. Dependent Variable: salary 9-10-month salary

These results are very similar, though we see the average salary is slightly higher and the difference between males and females is slightly less.

Now we prepare to conduct a hierarchical regression analysis using **sexd**, **leveld**, and **yearstt** as predictors. First, we examine the bivariate relationships and the correlations with both **salary** and **lnsal**. What do we see in the graphs and correlation table and what are the implications?

```
GRAPH
  /SCATTERPLOT(MATRIX)=salary lnsal sex leveld yearstt
  /MISSING=LISTWISE .

CORRELATIONS
  /VARIABLES=salary lnsal sexd leveld yearstt
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE .
```



The matrix scatterplot gives a very rough view of all bivariate relationships. We may wish to follow up with simple bivariate scatterplots of interesting pairs.

Correlations

		salary 9-10-month salary	lnsal = log of salary	sexd sexd (M=0;F=1)	leveld leveld (MA=0;PhD=1)	yearstt Estimated years in tenure track
salary 9-10-month salary	Pearson Correlation	1	.977**	-.179**	.242**	.689**
	Sig. (2-tailed)		.000	.000	.000	.000
	N	4558	4558	4558	4558	4558
lnsal = log of salary	Pearson Correlation	.977**	1	-.196**	.267**	.745**
	Sig. (2-tailed)	.000		.000	.000	.000
	N	4558	4558	4558	4558	4558
sexd sexd (M=0;F=1)	Pearson Correlation	-.179**	-.196**	1	-.011	-.256**
	Sig. (2-tailed)	.000	.000		.455	.000
	N	4558	4558	4558	4558	4558
leveld leveld (MA=0;PhD=1)	Pearson Correlation	.242**	.267**	-.011	1	.059**
	Sig. (2-tailed)	.000	.000	.455		.000
	N	4558	4558	4558	4558	4558
yearstt Estimated years in tenure track	Pearson Correlation	.689**	.745**	-.256**	.059**	1
	Sig. (2-tailed)	.000	.000	.000	.000	
	N	4558	4558	4558	4558	4558

**. Correlation is significant at the 0.01 level (2-tailed).

Look at the last three columns for the first row in the scatterplot matrix. These plots show relationships of the predictors with **salary**, our initial dependent variable. Look for potential violations of the assumptions for significance testing with regression. There may be an outlier, but with our large sample (n = 4558) the impact of one outlier of this magnitude is likely to be trivial. Error variances are not homogeneous for **leveld** or for **yearstt**, and there is a hint of curvilinearity. The second row shows these same relationships with the log of salary (**lnsal**). This variable seems a bit better suited for regression analysis because it shows less heteroscedasticity and perhaps slightly better linearity. The correlation matrix confirms that the correlation with **yearstt** is slightly larger with **lnsal** (r = .745) than with the untransformed variable **salary** (r = .689). We could ask for bivariate plots to examine these relationships more closely.

Reasonable people may disagree on whether to transform salary. An advantage of staying with the raw salary measure is that it is more intuitive and it is easier to use and explain results in the original metric. A disadvantage is that the regression model does not fit the data quite as well and assumptions for our statistical tests are not met as well. For example, the regression model assumes that the error in prediction is the same for all values of the predictors, but we can see error is larger for faculty with larger values of **yearstt** than those with smaller values.

A pragmatic approach is to analyze the data with different models to test the robustness of findings. If we obtain materially the same findings with alternate models, then we can be more confident in our conclusions and we can present the results in ways that communicate those findings clearly. If our results differ substantially, then we need to qualify our conclusions accordingly. The purpose of multiple analyses is to assess the sensitivity of our conclusions to various violations of assumptions – it is NOT a search for the smallest possible p value!

We will begin with a default hierarchical model on the raw salary data. Our primary interest is in the gender difference in faculty salary after we control for years in a tenure track job and type of academic program. We may use a different order of entry, depending on the question we wish to address. Entering **yearstt** first and **leveld** second, we enter **sexd** as our third predictor. This will provide a test of the sex difference in salary, controlling for the other two variables. In lay terms, what is the difference in salary for men and women who are equivalent in years on the job and the type of institution where they teach (Ph.D. granting or M.A. only).

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.689[a]	.475	.475	18,840.540	.475	4.119E3	1	4556	.000
2	.718[b]	.515	.515	18,103.518	.040	379.515	1	4555	.000
3	.718[c]	.515	.515	18,105.250	.000	.129	1	4554	.720

a. Predictors: (Constant), Estimated years in tenure track

b. Predictors: (Constant), Estimated years in tenure track, leveld (MA=0;PhD=1)

c. Predictors: (Constant), Estimated years in tenure track, leveld (MA=0;PhD=1), sexd (M=0;F=1)

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	45322.930	525.147		86.305	.000
	Estimated years in tenure track	2167.702	33.776	.689	64.179	.000
2	(Constant)	34265.298	759.475		45.117	.000
	Estimated years in tenure track	2130.109	32.512	.677	65.517	.000
	leveld (MA=0;PhD=1)	13923.201	714.702	.201	19.481	.000
3	(Constant)	34385.011	829.720		41.442	.000
	Estimated years in tenure track	2127.022	33.636	.676	63.237	.000
	leveld (MA=0;PhD=1)	13924.301	714.777	.201	19.481	.000
	sexd (M=0;F=1)	-203.650	568.098	-.004	-.358	.720

a. Dependent Variable: 9-10-month salary

Excluded Variables[c]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	leveld (MA=0;PhD=1)	.201[a]	19.481	.000	.277	.996
	sexd (M=0;F=1)	-.003[a]	-.264	.792	-.004	.934
2	sexd (M=0;F=1)	-.004[b]	-.358	.720	-.005	.934

a. Predictors in the Model: (Constant), Estimated years in tenure track

b. Predictors in the Model: (Constant), Estimated years in tenure track, leveld (MA=0;PhD=1)

c. Dependent Variable: 9-10-month salary

The Model Summary table indicates that **yearstt** is a very strong predictor of salary. By itself, years in a tenure track position accounts for 47.5% of the variance in salary (Model 1). The F Change is 4.119E3 which is 4119! (The E3 indicates multiplication by 10 to the power of 3, or 1000.) The level of the academic program **leveld** accounts for another 4.0% of the variance (R Square Change for Model 2). Most importantly for the purposes of our analysis, gender **sexd** does not add any additional predictive information. In fact, the F for the test of the R squared change is only .129 (Model 3), a bit less than what one would expect by chance (F = 1.000). On average, for faculty in our sample with the same **yearstt** and **leveld**, women are paid $203.65 less, but the standard error on this estimate is $568.098. A 95% confidence interval for the B weight is B ± (t)*(SE_B). For B on **sexd**, this gives -203.650 ± (1.9605)*(568.098) or ± 1172.57. Thus, our confidence interval ranges from -$1376 to +$698.92 for the population B value.

Similarly, the *t*-tests of the coefficients for Model 3 in the Coefficients table show that both **yearstt** and **leveld** are statistically significant, but **sexd** is not, indicating that the first two predictors each make unique contributions to prediction of salary, but gender does not. Model 1 in the Excluded Variables table shows that **sexd** did not add any useful information after **yearstt** was in the model, even before **leveld** was added.

Interpretation: There is no statistically significant difference in salary for men and women with the same number of years in tenure track. The correlation between **sexd** and **yearstt** is -.256 indicating that women on average have fewer years in tenure track positions.

As a sensitivity analysis, we replicate this analysis using **lnsal** as the dependent variable.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.745[a]	.554	.554	.20852	.554	5667.396	1	4556	.000
2	.777[b]	.604	.604	.19657	.050	571.680	1	4555	.000
3	.777[c]	.604	.604	.19659	.000	.435	1	4554	.510

a. Predictors: (Constant), yearstt Estimated years in tenure track

b. Predictors: (Constant), yearstt Estimated years in tenure track, leveld leveld (MA=0;PhD=1)

c. Predictors: (Constant), yearstt Estimated years in tenure track, leveld leveld (MA=0;PhD=1), sexd sexd (M=0;F=1)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	10.787	.006		1855.992	.000
	yearstt Estimated years in tenure track	.028	.000	.745	75.282	.000
2	(Constant)	10.640	.008		1290.225	.000
	yearstt Estimated years in tenure track	.028	.000	.731	78.298	.000
	leveld leveld (MA=0;PhD=1)	.186	.008	.223	23.910	.000
3	(Constant)	10.642	.009		1181.299	.000
	yearstt Estimated years in tenure track	.028	.000	.730	75.516	.000
	leveld leveld (MA=0;PhD=1)	.186	.008	.223	23.911	.000
	sexd sexd (M=0;F=1)	-.004	.006	-.006	-.660	.510

a. Dependent Variable: lnsal = log of salary

The findings are materially the same. Estimated years in tenure track (**yearstt**) is an even stronger predictor of **lnsal** (*r* = .745), accounting for 55.4% of the variance in **lnsal**. Program level (**leveld**) adds another 5.0%, bringing us up to an R squared value of .604. Again, **sexd** does not add any additional predictive information.

Note that **yearstt** has a larger *t*-value than **leveld**, yet B is larger for **leveld** than for **yearstt**. Why? Consider the scaling. The B coefficient indicates the predicted difference in **lnsal** for one unit difference on the predictor. One year doesn't add much, but **yearstt** acts over many years. The beta weights are for standardized predictors, so there we see a larger weight for **yearstt**.

We may be satisfied with our analyses and stop here, or we may wish to explore possible interactions among our predictors, or seek additional predictors such as academic concentration area of the faculty members (not available in this data set). Depending on our audience and our goals, we may present the results in text, tables, or graphics, or some combination. A basic descriptive graphic display is likely to be especially useful.

If we are concerned about possible interactions with sex, we may wish to run an ANOVA analyses on these data. We could code all of the interactions for regression analysis, but it is much easier to use ANOVA. For this analysis we will treat **rankcode** as a nominal variable rather than a continuous variable, and we will include lecturers. The regression analysis used only one df for **yearstt** and so was sensitive to only the linear component of **yearstt**, while the ANOVA analysis with *df* = 10 for **rankcode** is sensitive to all patterns across this variable.

```
UNIANOVA
  salary  BY sex level rankcode
  /METHOD = SSTYPE(3)
  /PLOT = PROFILE( rankcode*sex*level )
  /DESIGN = sex level rankcode sex*rankcode sex*level rankcode*level
sex*level*rankcode .
```

Tests of Between-Subjects Effects

Dependent Variable: salary 9-10-month salary

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	
Corrected Model	1.791E+012[a]	43	4.166E+010	139.750	.000	
Intercept	4.092E+012	1	4.092E+012	13729.683	.000	
sex	380610.332	1	380610.332	.001	.971	
level	4.533E+010	1	4.533E+010	152.072	.000	
rankcode	4.925E+011	10	4.925E+010	165.229	.000	
sex * rankcode	2343993697	10	234399369.7	.786	.642	
sex * level	29075948.4	1	29075948.37	.098	.755	
level * rankcode	2.726E+010	10	2726204021	9.146	.000	!
sex * level * rankcode	2470207217	10	247020721.7	.829	.601	
Error	1.371E+012	4598	298074787.4			
Total	2.812E+013	4642				
Corrected Total	3.162E+012	4641				

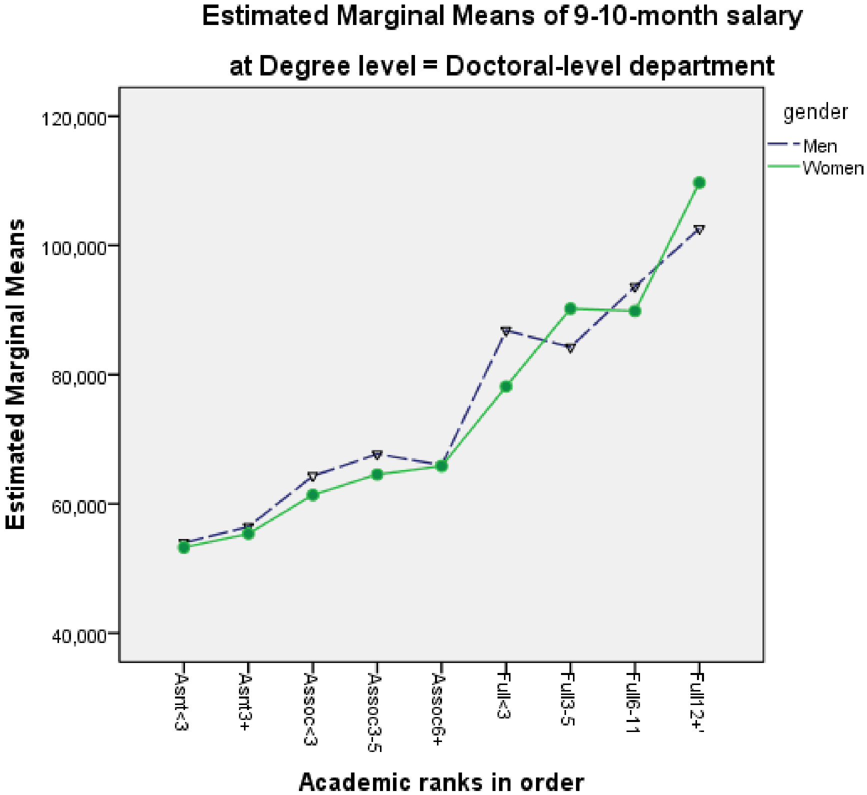
a. R Squared = .567 (Adjusted R Squared = .562)

Note that SPSS uses ‘scientific notation’ for very large (or very small) numbers, such as Sum of Squares for the Corrected Model. The number following E refers to the number of places the decimal point is shifted, either to the left (+) or the right (-). Thus, the Sum of Squares for the Corrected Model (1.791E+012) is 1,791,000,000,000.

This ANOVA used Type III Sum of Squares, which shows the unique contribution of each effect controlling for all other effects. We again see clear effects of **level** and **rankcode**, but no evidence of a unique **sex** effect, and there is no interaction between **sex** and either **rankcode** or **level**. However, the effects of **rankcode** are different for the two academic program levels. Plots are useful to provide an understanding of the nature of these effects and interactions.

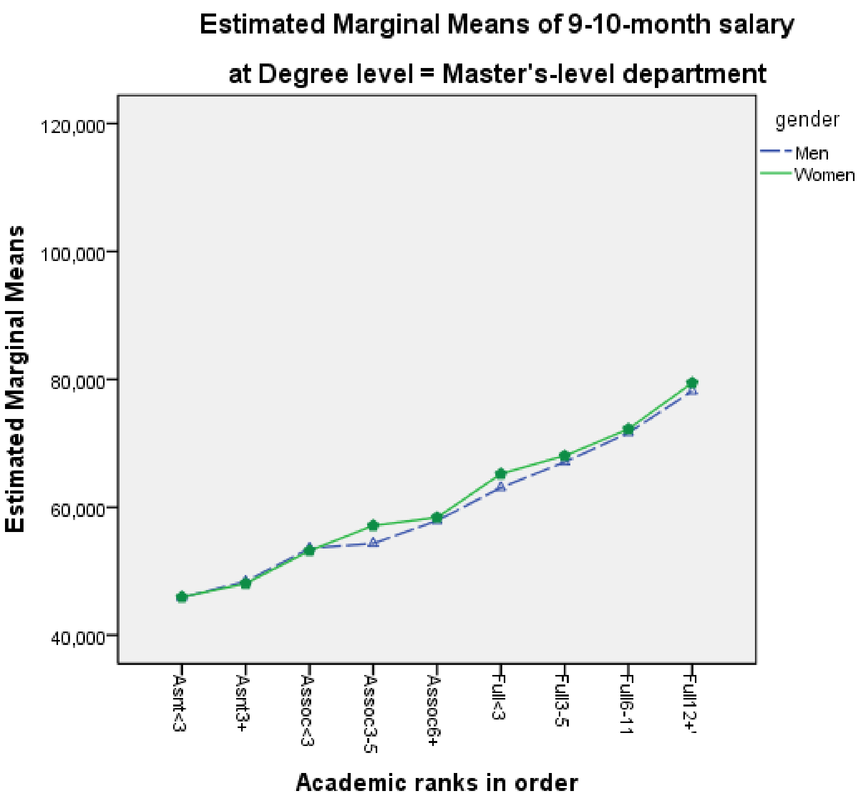
Within the SPSS chart editor, I changed the plot defaults to make the lines more distinctive, and I changed the scales to be the same for MA and PhD levels. From the graphs it is easy to see the strong effects of academic ranks and program level as well as the interaction between rank and program level. The linear relationship between rank and salary is stronger in Ph.D. programs; i.e., the difference between MA and Ph.D. salaries is greater at the higher ranks than lower ranks.

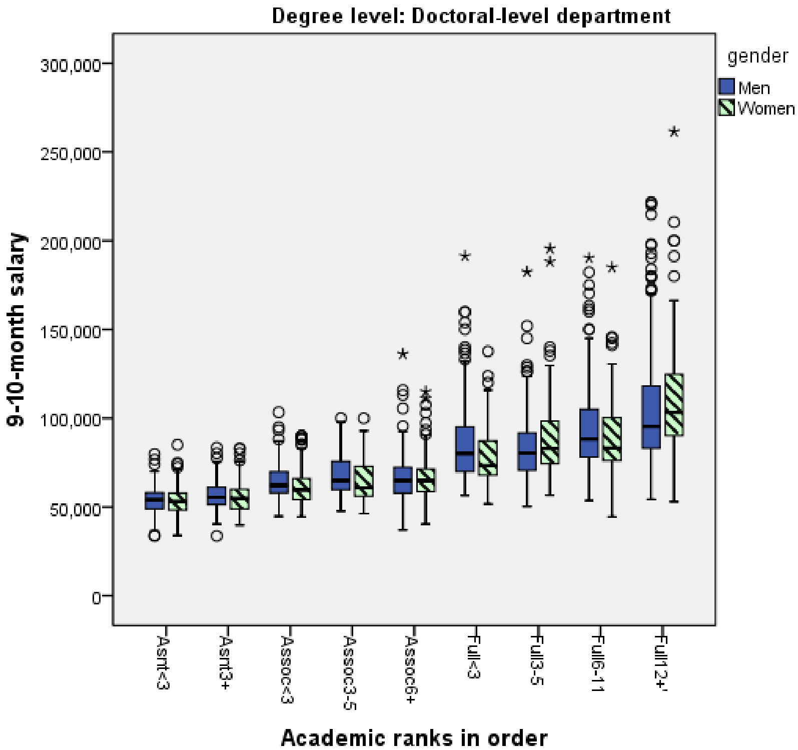
```
SORT CASES BY level .
SPLIT FILE  LAYERED BY level .
EXAMINE  VARIABLES=salary BY rankcode BY sex
 /PLOT=BOXPLOT /STATISTICS=NONE /NOTOTAL.
```

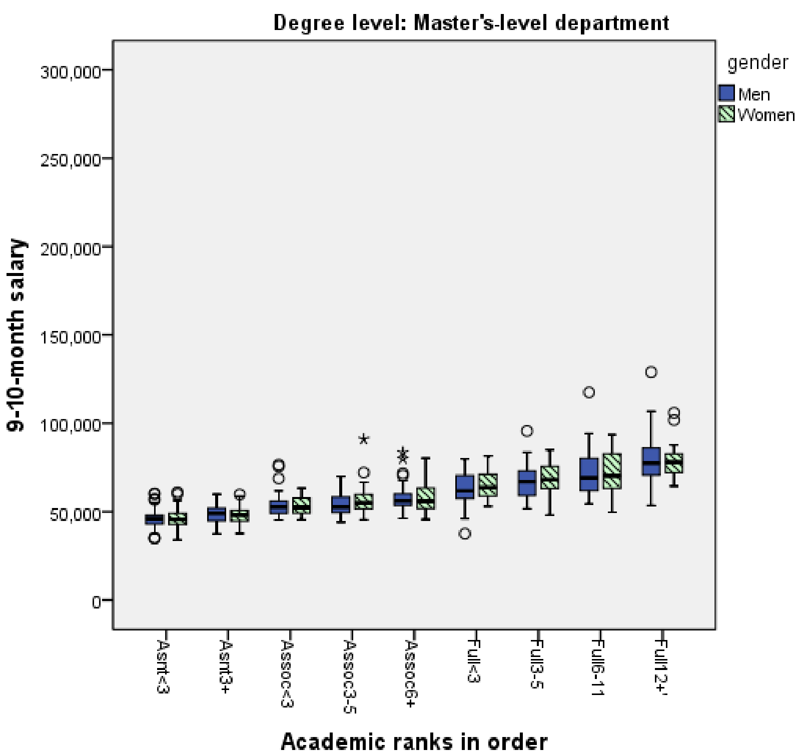


This is a plot of the data showing mean salary for each rank. Note that the horizontal axis does not have equal steps in terms of years. Yet we can use this graph to check our assumptions and verify that our model is appropriate.

An interesting anomaly is the somewhat lower mean for Associate Professors in rank for 6 or more years. This reflects lower salaries for people who do not advance on schedule.







Boxplots show more detail and can be very helpful for diagnostics as well as for presentations. In default SPSS output the scales are not necessarily equal, so first impressions can be misleading. It would look like salaries increase faster for Master's level programs. For naive audiences, and even for ourselves, it is good to rescale plots on the same scale if they are to be compared, as I have done here. I double clicked on the charts in the SPSS output to edit, changing the scales so both range from 0 to 300,000 in steps of 50,000, and I also changed the default color and texture for one of the groups to make the two groups easier to distinguish in black and white.

The key statistical findings of the analyses are summarized in Table 1, though there is quite a bit more that can be said about these data. In particular, the ANOVA indicates that we could do a better job of modeling salary by including the interaction between program level and years on the job. Also, we could do slightly better if we used the log of salary. However, for the purpose of assessing differences in salary between men and women, the Program Level by Year on Job interaction isn't consequential. It is appropriate that we checked for interactions with sex and the other predictor variables. If any interactions with sex had been present, they would impact our conclusions about sex differences. We could include these interactions within the regression model, but they would require coding of the interaction terms.

Table 1

Hierarchical Regression Predicting Psychology Faculty Salary with Years on Job, Academic Program Level, and Sex (N=4558)

Step	Variable	r	R^2 added	Final B	SE_B	Final beta
1	Years on Job	.689*	.475*	2127*	33.6	.676*
2	Program Level	.242*	.040*	13924*	715	.201*
3	Sex	-.179*	.000	-204	568	-.004
	(Constant)			34385*	830	

Cumulative R^2 = .515; adjusted R^2 = .515; Program Level is coded 0 = MA, 1 = PhD; Sex is coded 0 = Male, 1 = Female. Analysis is limited to psychology faculty in tenure track positions.
* $p < .001$

==

The figures on the next page show graphical representations of a mediation model based on a regression analysis that omits Program Level and uses arrow width to represent the relative strength of the paths. The first figure shows standardized path coefficients and the second shows raw B weight coefficients.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	14.873	.152		97.954	.000
	sexd sexd (M=0;F=1)	-4.334	.242	-.256	-17.887	.000

a. Dependent Variable: yearstt Estimated years in tenure track

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	77620.087	486.138		159.667	.000
	sexd sexd (M=0;F=1)	-9540.099	775.747	-.179	-12.298	.000
2	(Constant)	45415.370	631.183		71.953	.000
	sexd sexd (M=0;F=1)	-156.114	591.224	-.003	-.264	.792
	yearstt Estimated years in tenure track	2165.339	34.945	.688	61.963	.000

a. Dependent Variable: salary 9-10-month salary

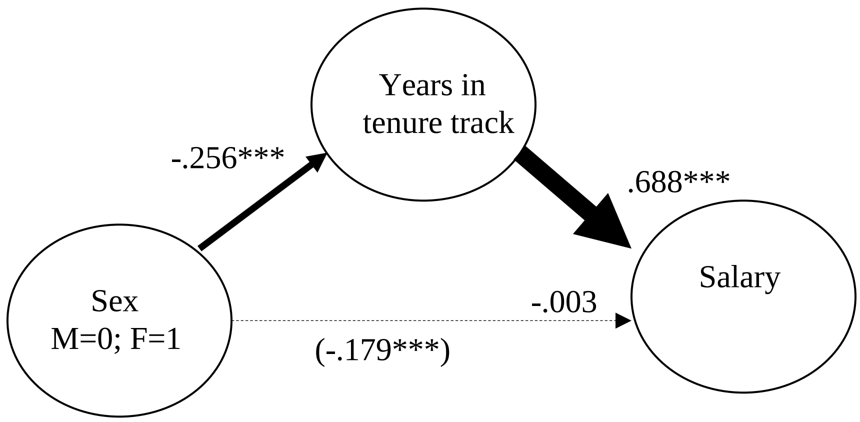


Figure 1
Standardized path coefficients showing Years in Tenure Track as a mediator of the relationship between Sex and Salary for Tenure-track Graduate Faculty in Psychology (N = 4558). (Direct effect is shown in parentheses.) ***p < .001

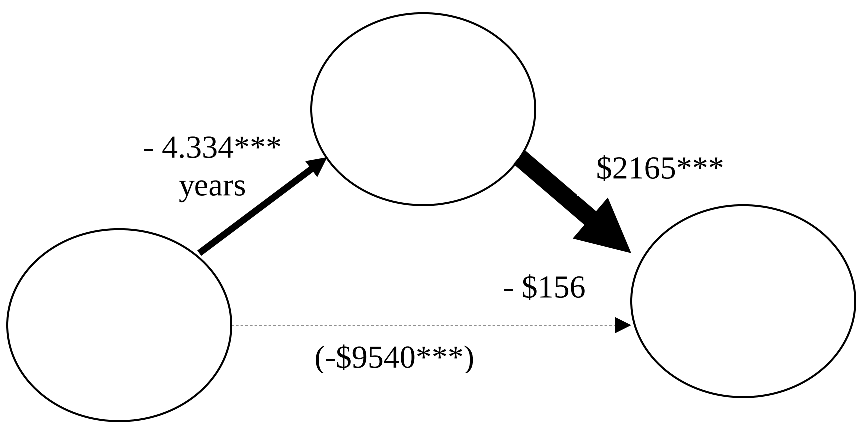


Figure 2
Unstandardized path coefficients showing Years in Tenure Track as a mediator of the relationship between Sex and Salary for Tenure-track Graduate Faculty in Psychology (N = 4558). (Direct effect is shown in parentheses.) ***p < .001