

# Moderation & Interaction

Lecture 5

Multivariate statistics

Psychology 613 – Spring 2022

# Moderation

Suppose:

X is an IV

M is a moderator

Y is a DV

*Moderation* is when the relationship between X and Y changes as a function of M.

In this case, X and M are said to *interact* in predicting Y.

# Moderation: Example

Group	Control	Treatment 1	Treatment 2	MEAN
Bajorans	30	50	100	60
Cardassians	30	100	50	60
MEAN	30	75	75	

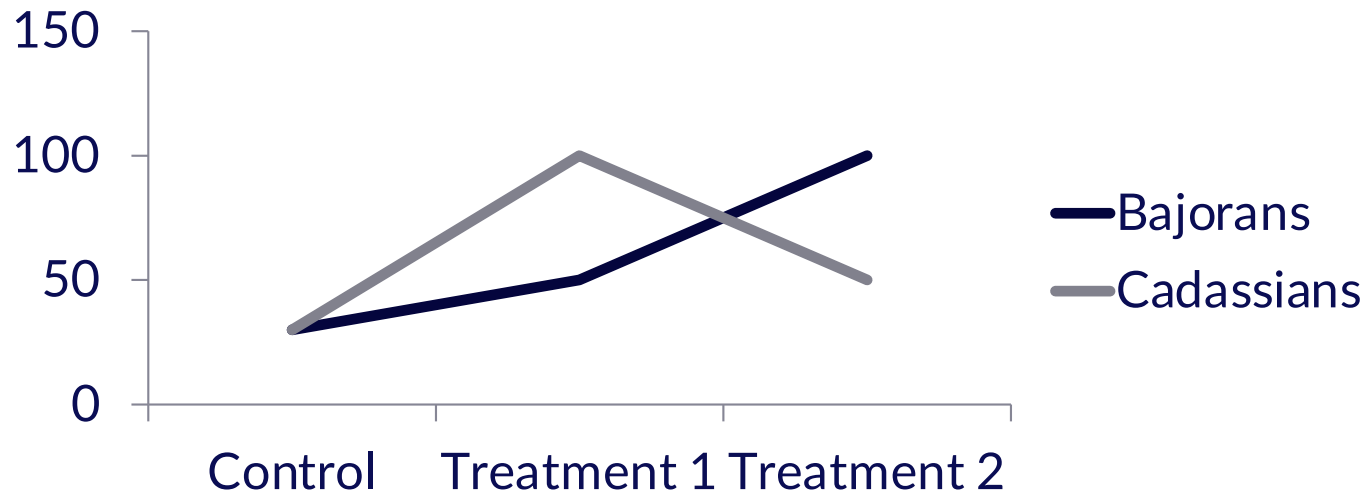
No main effect of species

Main effect of treatments vs. control

Huge interaction of species by treatments

- The effect of treatment depends on species
- Treatment and species *interact* in predicting outcome
- Species *moderates* the effect of treatment

# Moderation: Example



No main effect of species

Main effect of treatments vs. control

Huge interaction of species by treatments

- The effect of treatment depends on species
- Treatment and species *interact* in predicting outcome
- Species *moderates* the effect of treatment

# Moderation in regression

Typically, we assume simple additivity:

$$Y = b_0 + b_1X1 + b_2X2 + e$$

→ The effect of X1 (over and above X2) is the same regardless of the level of X2.

However, X1 may not operate the same way across the entire range of X2; particular combinations of X1 and X2 may produce specific effects (*interactions*).

The effect of one variable may depend on the level of the other.

# Moderation in regression

Moderation model:

$$Y = b_0 + b_1X1 + b_2X2 + b_3(X1*X2) + e$$

→ The unique effect of X1 may vary as a function of X2.

$b_0$ : The expected value of Y when X1, X2, and  $X1X2 = 0$ .

$b_1$ : The “main” effect of X1 controlling for X2 and  $X1X2$ .

$b_2$ : The “main” effect of X2 controlling for X1 and  $X1X2$ .

$b_3$ : The interaction (i.e., joint effect) of X1 and X2 controlling for X1 and X2.

*Reflects how, say, the  $Y \sim X1$  relationship changes with X2*

# Example!



The image is a screenshot of the Nature journal website. At the top, the word "nature" is written in a large, white, serif font on a dark red background. To its right, in a smaller white font, is the text "International weekly journal of science". Below this, a horizontal navigation bar contains several links: "Home", "News & Comment", "Research", "Careers & Jobs", "Current Issue", "Archive", "Audio & Video", and "For". Below the navigation bar, a series of dark grey arrows point to the right, containing the text "News & Comment", "News", "2014", "April", and "Article". Below this, the text "NATURE | NEWS" is displayed in a blue, sans-serif font. To the right of this text are three small icons: a share icon, an email icon, and a print icon. The main headline is "Male researchers stress out rodents" in a large, bold, black font. Below the headline is a sub-headline in a smaller, bold, black font: "Rats and mice show increased stress levels when handled by men rather than women, potentially skewing study results." Below the sub-headline is the author's name, "Alla Katsnelson", in a blue, sans-serif font. At the bottom left, the date "28 April 2014" is displayed in a black, sans-serif font.

**nature** International weekly journal of science

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News & Comment > News > 2014 > April > Article

**NATURE | NEWS**

**Male researchers stress out rodents**

**Rats and mice show increased stress levels when handled by men rather than women, potentially skewing study results.**

**Alla Katsnelson**

28 April 2014

# Centering alters interpretation

**Uncentered:**  $Y = b_0 + b_1X_1 + b_2X_2 + b_3X_1*X_2$

$b_1$ : slope of Y on X1 when  $X_2 = 0$

$b_2$ : slope of Y on X2 when  $X_1 = 0$

$b_3$ : partialled interaction

**Centered:**  $Y = b_0 + b_1X_{1_{cen}} + b_2X_{2_{cen}} + b_3X_{1_{cen}}*X_{2_{cen}}$

$b_1$  = slope of Y on X1 at average of X2

The average regression of Y on X1 across range of X2

$b_2$  = slope of Y on X2 at average of X1

The average regression of Y on X2 across range of X1

$b_3$  = partialled interaction



# Center and interact

<u>Var 1</u>		<u>Var 2</u>		<u>Interaction term (product)</u>
X1-m <sub>X1</sub>	*	X2-m <sub>X2</sub>	→	(X1-m <sub>X1</sub> )*(X2-m <sub>X2</sub> )
D1	*	X2-m <sub>X2</sub>	→	(D1)*(X2-m <sub>X2</sub> )
D1	*	D2	→	D1 * D2
D1,D2	*	X2-m <sub>X2</sub>	→	D1(X2-m <sub>X2</sub> ), D2(X2-m <sub>X2</sub> )
D1,D2	*	D3,D4	→	D1D3,D1D4,D2D3,D2D4

# Interpretation tips

In equations with higher-order terms (e.g., interactions), variability shared by higher- and lower-order terms is typically attributed to the lower-order term.

Interpret coefficients of lower-order terms at zeros for all other variables.

# Interaction: Procedure

## Step 1

The initial analysis focuses on determining whether or not the interaction is significant.

If there is a single interaction variable, examine the t-test for the associated b coefficient.

If multiple vectors code for the interaction (e.g., dummy variables), test simultaneously with  $R^2$  change test from nested models.

# Interaction: Procedure

## Step 2a: Interaction is non-significant

- Non-significant interaction: the effects of each variable are constant across the range of the other
- Follow-up with tests of main effects, which collapse across values of the other variable.

## OR Step 2b: Interaction is significant

- Significant interaction: the effect of one variable changes with the value of another
- Follow-up with tests of simple effects, which are conducted *at particular values* of the other variable.

# Interaction: Procedure

## Step 3a: No interaction

Examine effect of  $X_1$  on  $Y$  at:

$X_2 = \text{mean}$

$X_2 = +1 \text{ SD}$

$X_2 = -1 \text{ SD}$

$$Y = b_0 + b_1X_1 + b_2X_2$$

Rearrange terms:  $Y = (b_0 + b_2X_2) + b_1X_1$

→ *With no interaction, intercept changes with  $X_2$  but the slope of  $X_1$  on  $Y$  does not*

# Interaction: Procedure

## Step 3b: Significant interaction

Examine effect of X1 on Y at:

X2 = mean

X2 = +1 SD

X2 = -1 SD

$$Y = b_0 + b_1X1 + b_2X2 + b_3X1X2$$

Rearrange terms:  $Y = (b_0 + b_2X2) + X1(b_1 + b_3X2)$

→ *With an interaction, intercept AND SLOPE of X1 on Y change with X2.*

# Interaction: Example

- Predicting adolescents' sexual behavior from their sexual attitudes and agreeableness
  - Sexual attitudes: Sexual Opinion Survey (SOS)
  - Agreeableness: “a” from Big Five Inventory
  - Behavior: Sociosexual Orientation Inventory (SOI)

2. With how many different partners have you had sexual intercourse on *one and only one* occasion?

<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
0	1	2	3	4	5-6	7-9	10-19	20 or more

CORRELATION  
MATRIX - RAW

	Sexual behavior	Sexual attitudes	Agreeableness	Interaction
	soitot	sos	a	sosXa
soitot	1.0000000	0.4821981	-0.2235485	0.3185900
sos	0.4821981	1.0000000	-0.1987734	0.8325501
a	-0.2235485	-0.1987734	1.0000000	0.3564782
sosXa	0.3185900	0.8325501	0.3564782	1.0000000

CORRELATION  
MATRIX - Centered

	soitot	Zsos	Za	sosXa_cent
soitot	1.0000000	0.4821981	-0.2235485	-0.0830690
Zsos	0.4821981	1.0000000	-0.1987734	0.0355601
Za	-0.2235485	-0.1987734	1.0000000	0.0851186
sosXa_cent	-0.0830690	0.0355601	0.0851186	1.0000000



## REGRESSION RESULTS - RAW

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	-3.0269282	1.3295076	-2.277	0.02355	*
sos	0.0520891	0.0166726	3.124	0.00197	**
a	0.0294081	0.0306397	0.960	0.33797	
sos:a	-0.0006718	0.0003893	-1.726	0.08548	.
---					

## REGRESSION RESULTS - Centered

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	-0.0318105	0.0527445	-0.603	0.5469	
c_sos	0.0239538	0.0027222	8.799	<2e-16	***
c_a	-0.0200553	0.0084629	-2.370	0.0185	*
sosXa_cent	-0.0006718	0.0003893	-1.726	0.0855	.
---					

# Fit the model: 2 MEs + 1 Int

Call:

```
lm(formula = soitot ~ c_sos + c_a + sosXa_cent)
```

Residuals:

Min	1Q	Median	3Q	Max
-1.9874	-0.6363	-0.1924	0.4840	3.3481

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-0.0318105	0.0527445	-0.603	0.5469
c_sos	0.0239538	0.0027222	8.799	<2e-16 ***
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---

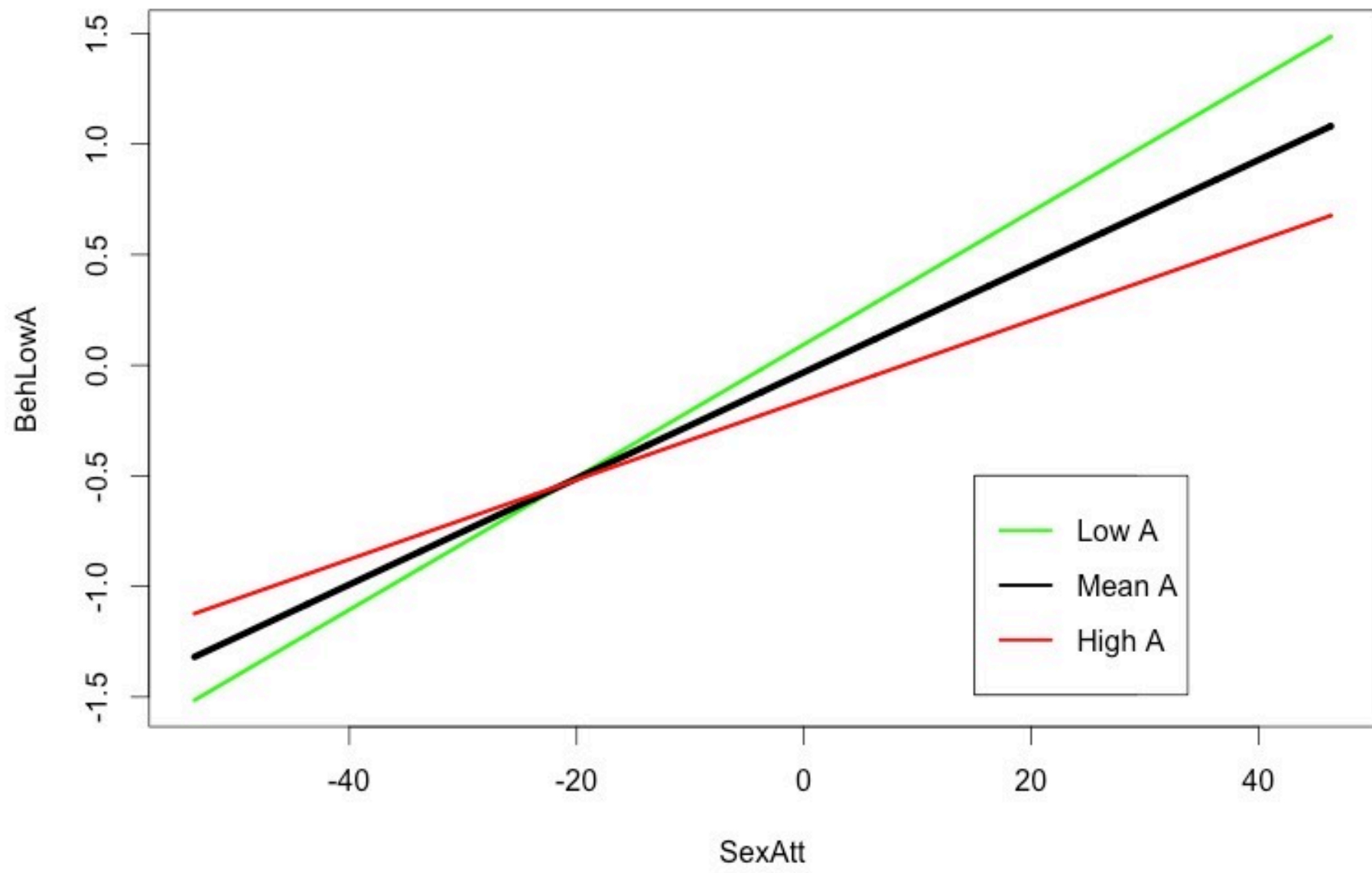
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

# Visualization with simple slopes

- Create one variable with the range of sexual attitudes (20 -> 120, **centered**)
- Create three more variables based on the simple slope equations:  
High “a”: BehHighA <-  $-.158 + .018 * \text{SexAtt}$   
Mean “a”: BehMeanA <-  $-.032 + 0.024 * \text{SexAtt}$   
Low “a”: BehLowA <-  $.094 + .03 * \text{SexAtt}$

# Visualization with simple slopes

```
> SexAtt <- seq(20, 120, by=.1) - 73.6237
> BehHighA <- -.158 + SexAtt*.018
> BehMeanA <- -.032 + SexAtt*.024
> BehLowA <- .094 + SexAtt*.03
> plot(SexAtt,BehLowA, type="l", col="green", lwd=3)
> lines(SexAtt,BehMeanA, type="l", col="black", lwd=5)
> lines(SexAtt,BehHighA, type="l", col="red", lwd=3)
> legend(15,-.5,c("Low A","Mean A", "High A"),
      lty=c(1,1,1), lwd = c(3,5,3),
      col=c("green", "black","red"))
```



# Invariance of interpretation

Note that the **interpretation of the slopes** is the same regardless of centering.

E.g., for uncentered params:

$$\text{SexBeh} = (-3.03 + .029a) + \text{SexAtt}(.052 - .001a)$$

At mean:

$$\text{SexBeh} = (-3.03 + .029(42)) + \text{SexAtt}(.052 - .001(42))$$

$$\text{SexBeh} = -1.8 - \text{SexAtt}^*.024 \quad \text{Centered}$$

– Mean “a”: SexBeh <- -.032 + 0.024\*SexAtt

# Significance testing of simple slopes

Need variance/covariance matrix of regression coefficients (Add “/STATISTICS BCOV” to “REGRESSION” syntax)

$$SE_{b\_at\_X2} = \sqrt{SE_{b1}^2 + 2 * X2(cov(b_1, b_3)) + X2^2 SE_{b3}^2}$$

$$t_{b\_at\_X2} = (b_1 + b_3 X2) / SE_{b\_at\_X2}$$

Distributed ~t with N-K-1 df

# Significance testing of simple slopes

```
> vcov(full_model)
```

	(Intercept)	c_sos	c_a	c_sos:c_a
(Intercept)	2.781978e-03	-1.385954e-06	-7.547667e-06	3.687111e-06
c_sos	-1.385954e-06	7.410307e-06	4.668899e-06	-5.696186e-08
c_a	-7.547667e-06	4.668899e-06	7.162083e-05	-3.101022e-07
c_sos:c_a	3.687111e-06	-5.696186e-08	-3.101022e-07	1.515570e-07

Covariances

Variances (=SE<sup>2</sup>)



# Significance testing of simple slopes

Test high “a” slope:

$b_1$  = effect of attitudes  
 $b_2$  = effect of “a”  
 $b_3$  = interaction

$$SE_{b\_at\_X2} = \sqrt{SE_{b1}^2 + 2 * X2(\text{cov}(b_1, b_3)) + X2^2 SE_{b3}^2}$$

$$SE_{b\_at\_X2} = \sqrt{.0000007^2 + 2 * X2(-.000000005) + X2^2 *.00000002^2}$$

$$t_{b\_at\_X2} = (b_1 + b_3 X2) / SE_{b\_at\_X2}$$

$$t_{b\_at\_highA} = (.024 - .001 * 6.3) / .0003 = 5.9$$

# Continuous/categorical interactions

Compute interaction terms in the same way

Always center continuous predictors

No need to center categorical variables (since interpretation of “mean” of a categorical variable is meaningless)

# Cont/Cat interaction: Example

The “salary” dataset on Canvas

Faculty salary data from the early 1980s  
(though sadly unchanged)

Includes other variables of interest such as #  
of publications, gender, and citations.

# Cont/Cat interaction: Example

Predict faculty salary based on # of publications, gender, and their interaction.

Call:

```
lm(formula = salary ~ c_pubs + female + c_pubs * female)
```

Residuals:

Min	1Q	Median	3Q	Max
-12950	-6583	239	6003	21408

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	55649.48	1394.00	39.921	< 2e-16	***
c_pubs	446.80	91.39	4.889	8.39e-06	***
femaleFemale	-2794.01	2130.06	-1.312	0.1948	
c_pubs:femaleFemale	-350.19	163.36	-2.144	0.0363	*

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

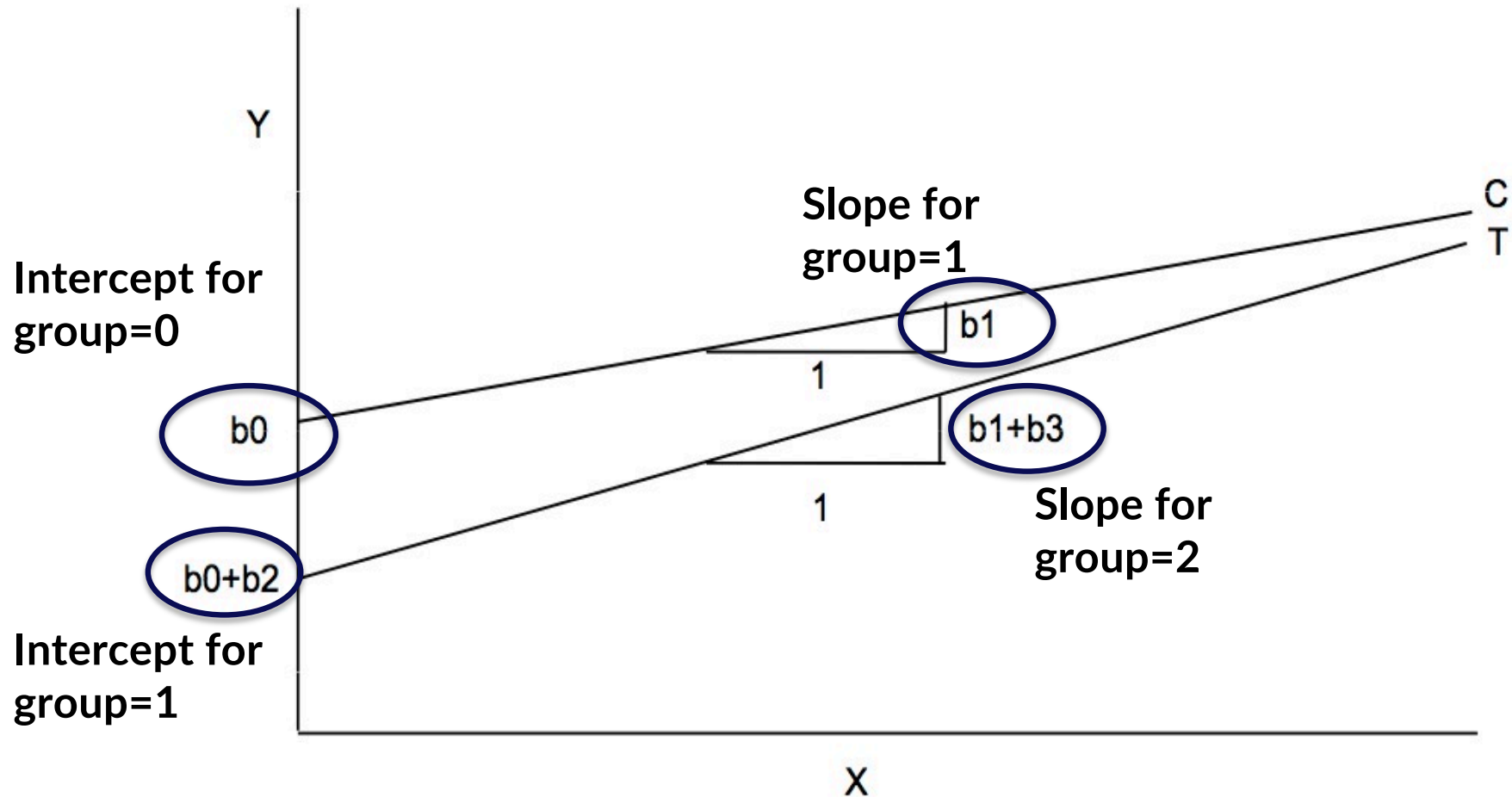
# Cont/Cat interaction: Example

$$\begin{aligned}\text{Salary} = & 55,650 + 446*\text{pubs} - 2794*\text{female} \\ & \dots - 350*\text{pubs}*\text{female}\end{aligned}$$

$$\begin{aligned}\text{Male salary (female=0):} \\ = & 55,650 + 446*\text{pubs}\end{aligned}$$

$$\begin{aligned}\text{Female salary (female=1):} \\ = & (55,650-2794) + (446-350)*\text{pubs}\end{aligned}$$

# General Cont/Cat graph



# Cont/Cat interaction: Example

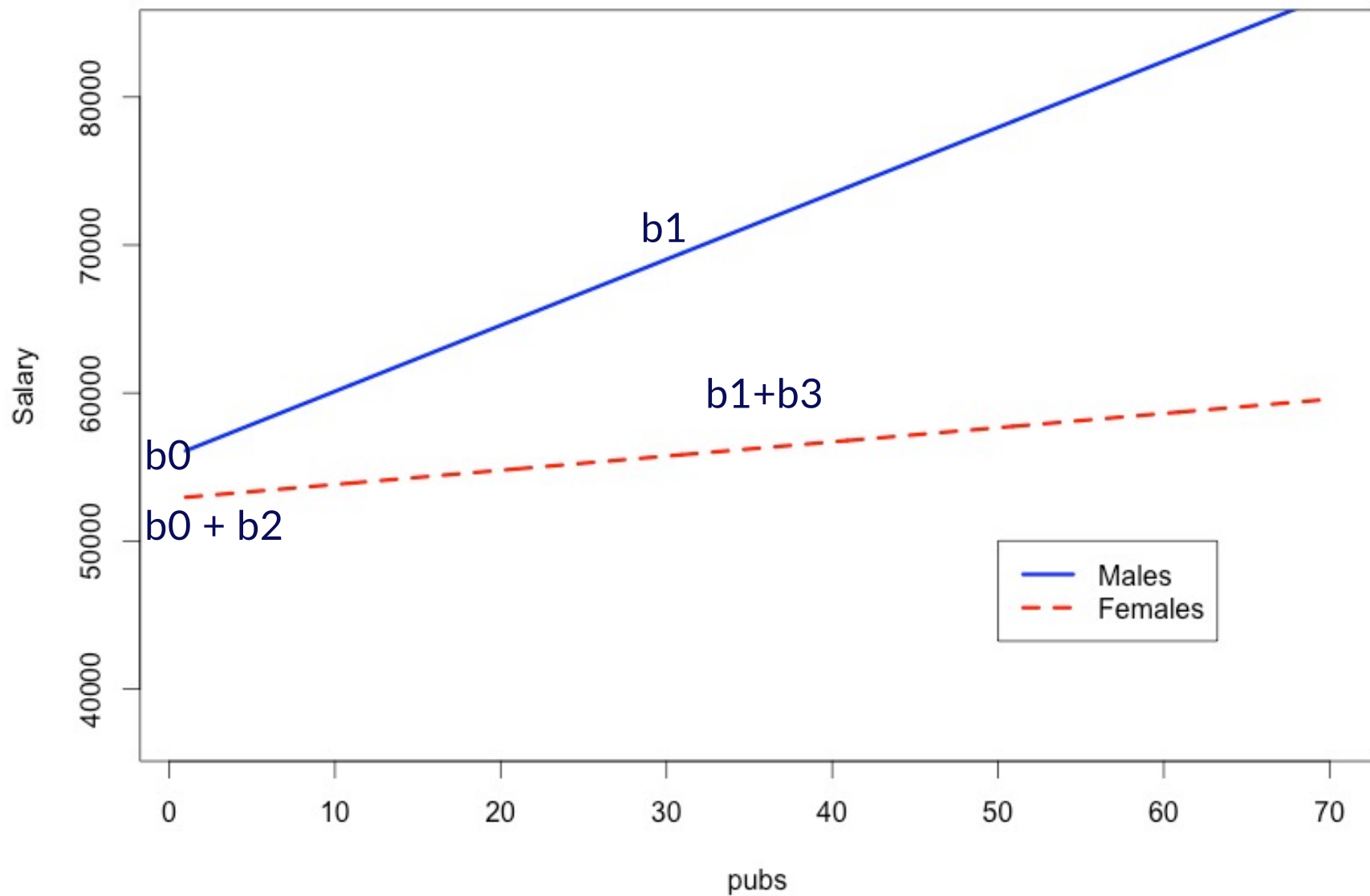
- $b_1$  represents the *difference* in intercepts between the groups
  - Significance test compares group intercepts
- $b_3$  represents the *difference* in slopes
  - Significance test compares group slopes

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	55649.48	1394.00	39.921	< 2e-16 ***	
c_pubs	446.80	91.39	4.889	8.39e-06 ***	$b_1$ test
femaleFemale	-2794.01	2130.06	-1.312	0.1948	
c_pubs:femaleFemale	-350.19	163.36	-2.144	0.0363 *	$b_3$ test
---					

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

# In this case...





# Cont/Cat Interaction: Example

Tests of simple effects (i.e., for each gender separately):

**Could:** test simple slopes as above

**Easier:** split sample, regress outcome on predictor (i.e., salary on pubs), then compute the F-test based on MS-predictor (from simple model) and MS-error (from larger model).

# Cont/Cat Interaction: Example

R: Mdata = subset(dataset, female=0)

Males

```
Response: salary
      Df    Sum Sq Mean Sq F value    Pr(>F)
c_pubs  1 1599322474 1599322474 22.442 3.993e-05 ***
Residuals 33 2351778342  71266010
---
```

Females

```
Response: salary
      Df    Sum Sq Mean Sq F value    Pr(>F)
c_pubs  1  34062834 34062834  0.5568 0.4625
Residuals 25 1529377297 61175092
```

# Cont/Cat Interaction: Example

## Full model

Response: salary

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
c_pubs	1	1472195326	1472195326	22.0005	1.702e-05	***
female	1	85752814	85752814	1.2815	0.26228	
c_pubs:female	1	307516045	307516045	4.5955	0.03626	*
Residuals	58	3881155638	66916477			
---						

For males:  $F(1,58) = 1.6b / 67m = 24, p < .001$

For females:  $F(1,58) = 34m / 67m = 0.50, p \text{ ns}$

# Types of interactions

Synergistic (enhancing) interactions

All three terms in same direction

Buffering interaction

Predictors of opposite sign

Risk and protective factors

Antagonistic interaction

Predictors same sign, interaction opposite sign

Total influence is less than sum of the parts

e.g., Ability + Hard with  $-$  (ability\*hard work)

# Final notes on interactions

- There is no test of difference between simple slopes
- Only interpret interactions within the range of data
- Do not interpret beta weights with interaction in the equation (use simple slopes)
- All lower-order terms must be in the model to interpret an interaction