



Statistical Interaction / Effect Modification

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Learning Objectives

To be able to:

- 1. Define interaction
- 2. Understand the difference between confounding and interaction
- 3. Know how to test for interaction
- 4. Know how to deal with interaction in your analyses



Definitions

Interaction

- Interaction occurs when the presence of one factor modifies the effect of another on an outcome
- i.e. the effect of the exposure **differs** according to which category of the **other factor** is being examined

Confounding

- Occurs when an association between an exposure and an outcome is mixed up with the effect of another exposure on the outcome, and the two exposures are related to one another
- For something to be a confounder, it must be associated with the exposure and independently associated with the outcome







Confounding vs. Interaction

Confounding

- Concerned with 'alternative explanations' for an effect of an exposure on outcome
- We aim to remove the influence of a confounder in order to get nearer the 'truth'
- You control for confounding factors
- There is no statistical test for confounding

Interaction

- An *important property* of the relationship between two factors, and their influence on an outcome
- You do not try to eliminate this effect, instead you want to detect and describe interaction in the greatest possible detail
- You stratify by effect modifiers
- There is a statistical test for interaction





An example: Confounding Coffee consumption and Cancer

Exposure Outcome

Coffee consumption Cancer





An example: Confounding Coffee consumption and Cancer

Exposure Outcome

Coffee consumption Cancer

	Coffee	No coffee
Cases (Cancer)	450	300
Controls (No cancer)	200	250





An example: Confounding Coffee consumption and Cancer

Exposure Outcome

Coffee consumption Cancer

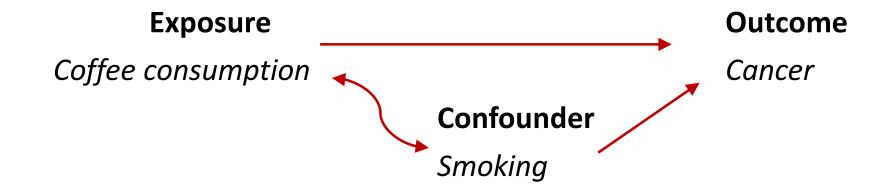
	Coffee	No coffee		
Cases (Cancer)	450	300	= <u>450/300</u> =	
Controls (No cancer)	200	250	200/250	0.8

Odds Ratio = 1.9





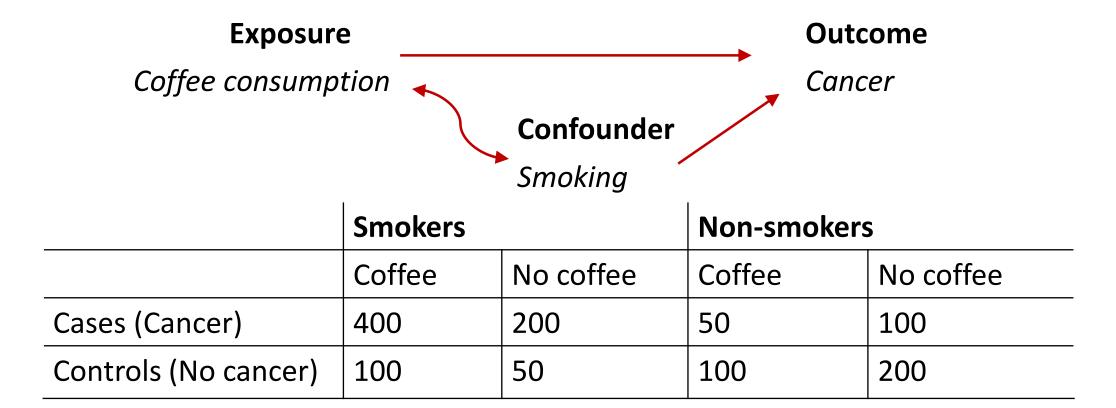
An example: Confounding Coffee consumption and Cancer







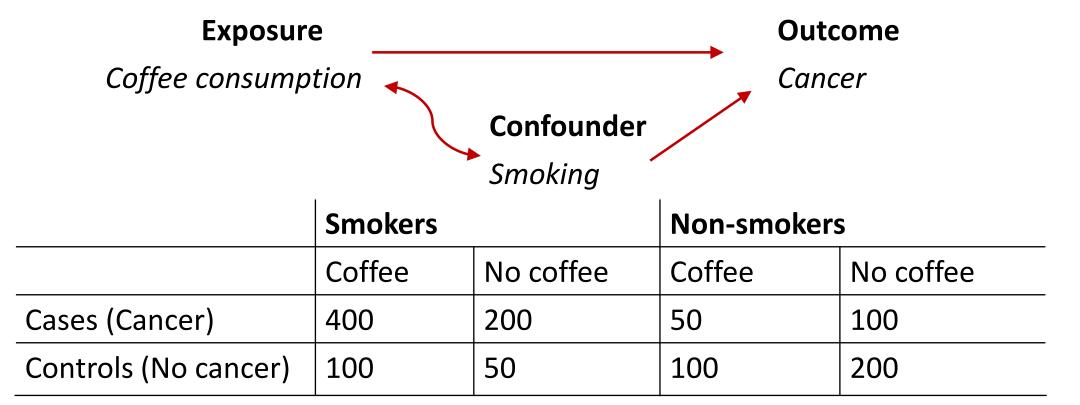
An example: Confounding Coffee consumption and Cancer







An example: Confounding Coffee consumption and Cancer



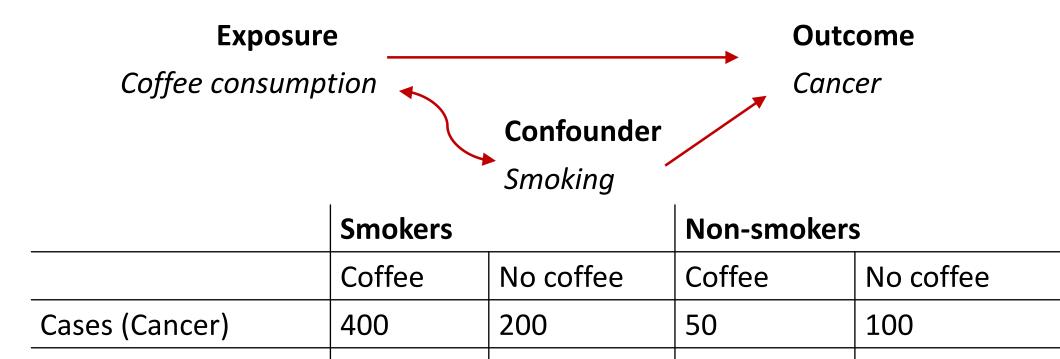
Odds Ratio = 1.0

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An example: Confounding Coffee consumption and Cancer



50

Odds Ratio = 1.0

100

Odds Ratio = 1.0

200

100

Conclusion:

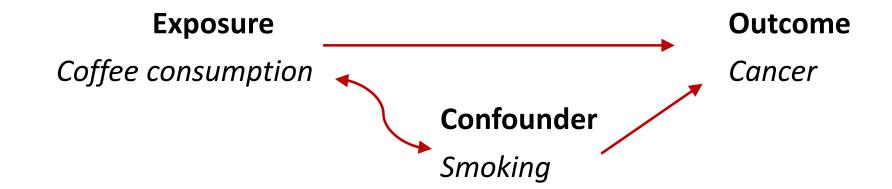
Controls (No cancer)

Smoking is totally confounding the association between coffee drinking and cancer



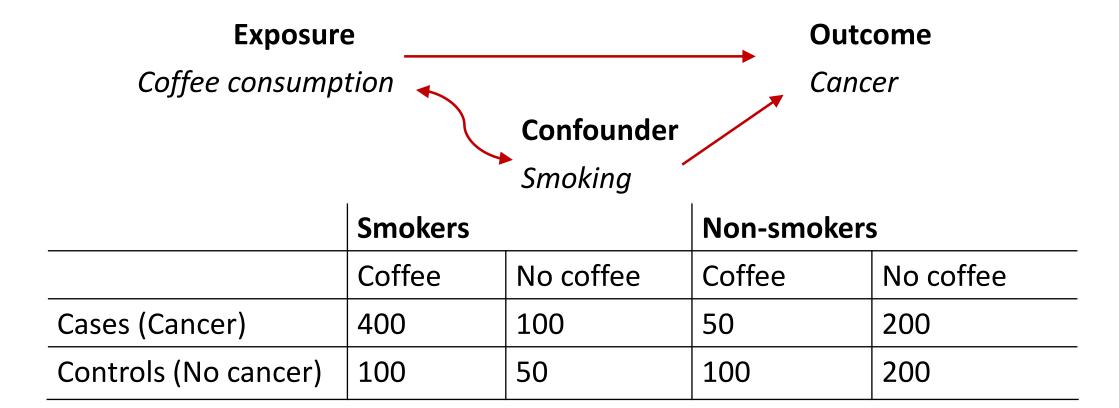






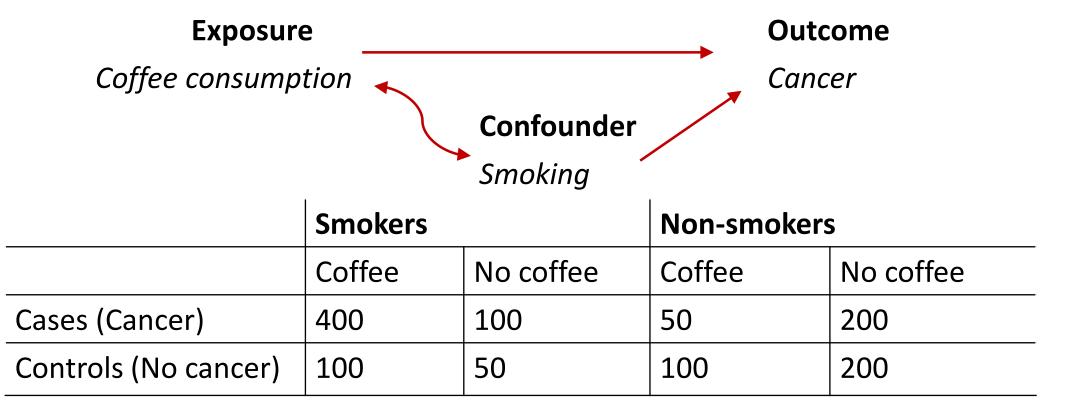










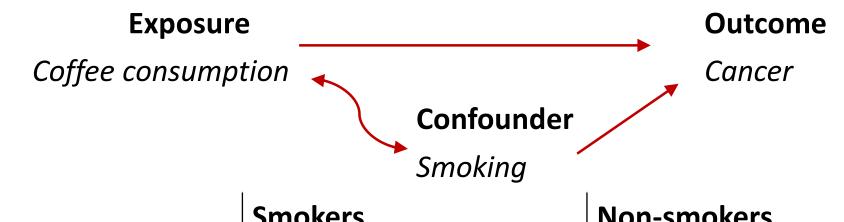


Odds Ratio = 2.0

Odds Ratio = 0.5







	Smokers		Non-smokers	
	Coffee	No coffee	Coffee	No coffee
Cases (Cancer)	400	100	50	200
Controls (No cancer)	100	50	100	200

Odds Ratio = 2.0

Odds Ratio = 0.5

Conclusion:

Smoking modifies the effect of coffee drinking on cancer





- A study of sexual behaviours and risk of HIV infection
- 400 men with HIV recruited from general medical clinic
- 400 men coming to clinic and testing negative for HIV also recruited
- All were asked about number of sexual partners and condom use
- Study design?





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Case-control study design





		HIV +	HIV -
Number of sexual	≥5	200	100
partners in past	<5	200	300
5 years			





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5 years			

Odds ratio: 3.0





		HIV +	HIV -	= <u>200/100</u>
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Men who report *always* using a condom

Men who report not always using a condom





		HIV +	HIV -	= <u>200/100</u>
Number of sexual	≥5	200	100	200/300
partners in past 5 years	<5	200	300	Odds ratio: 3.0

Men who report *always* using a condom

		HIV +	HIV -
Number of sexual	≥5	50	60
partners in past	<5	80	140
5 years			

Men who report *not always* using a condom

	HIV +	HIV -
≥5	150	40
<5	120	160
	≥5	





		HIV +	HIV -	= <u>200/100</u>
Number of sexual	≥5	200	100	200/300
partners in past 5 years	<5	200	300	Odds ratio: 3.0

Men who report *always* using a condom

		HIV +	HIV -
Number of sexual	≥5	50	60
partners in past	<5	80	140
5 years			

Odds ratio: 1.45

Men who report not always using a condom

		HIV +	HIV -
Number of sexual	≥5	150	40
partners in past 5 years	<5	120	160

Odds ratio: 5.0





		HIV +	HIV -	= <u>200/100</u>
Number of sexual	≥5	200	100	200/300
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Odds ratio: 1.45

Men who report *not always* using a condom

		HIV +	HIV -
Number of sexual	≥5	150	40
partners in past	<5	120	160
5 years			

Odds ratio: 5.0

Conclusion: there is an interaction between the number of sexual partners and condom use on the odds of HIV infection

i.e. reporting using a condom *modifies the effect* of the number of sexual partners on the odds of HIV infection, so that reporting condom use lowers the effect of higher sexual partner number on the odds of HIV infection







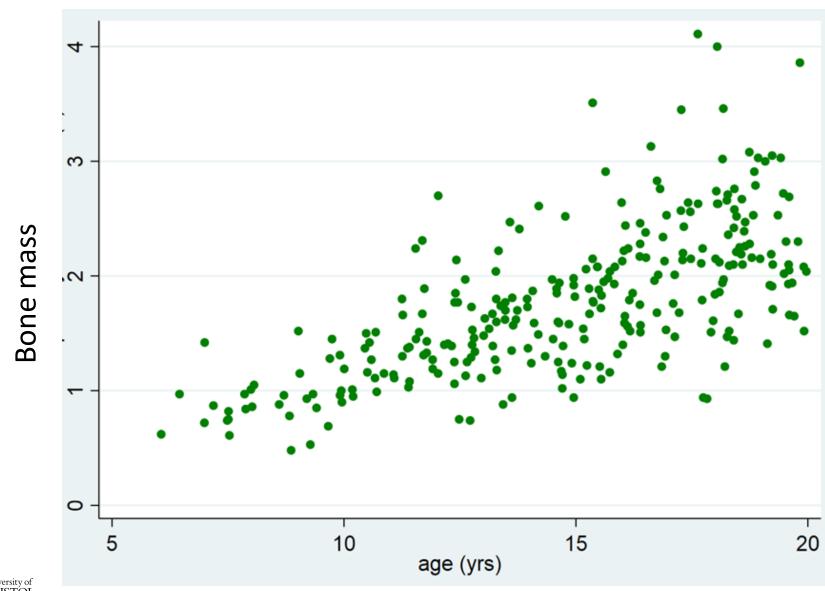
Summary

		Crude odds/ rate/ risk ratio	Odds/ rate/ risk ratio in Stratum 1	Odds/ rate/ risk ratio in Stratum 2	Adjusted odds/ rate/ risk ratio
Example 1	No confounding No interaction	3.0	3.0	3.0	3.0
Example 2	Confounding No interaction	3.0	2.0	2.0	2.0
Example 3	Interaction	3.0	0.8	5.5	Should not be calculated





Now thinking about continuous data

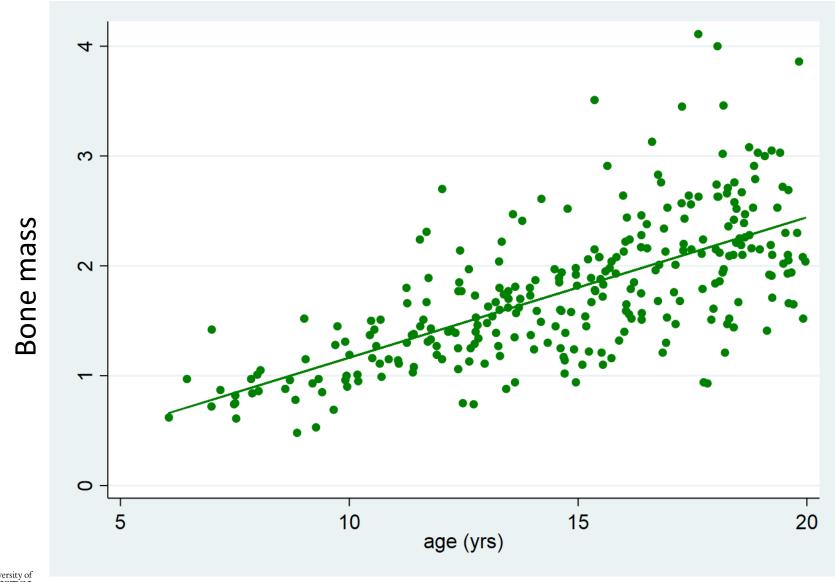








Adding a line of best fit

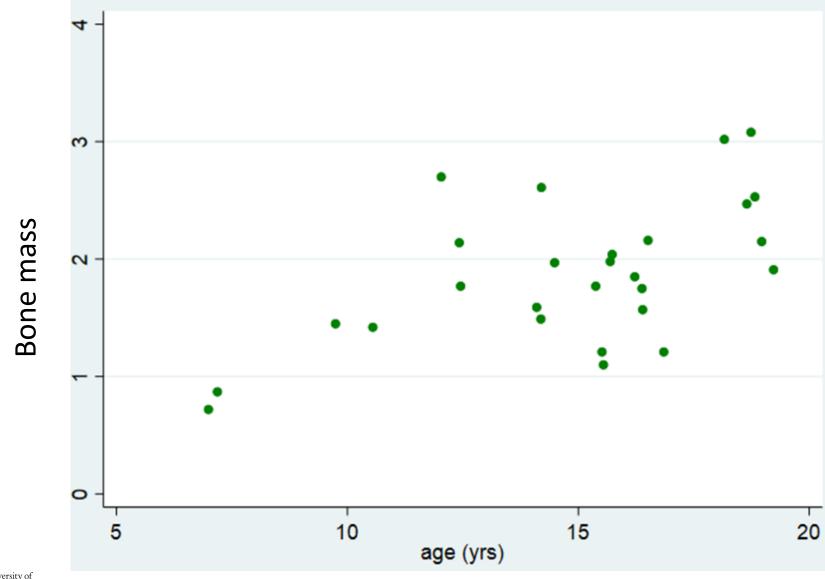








Adding a line of best fit

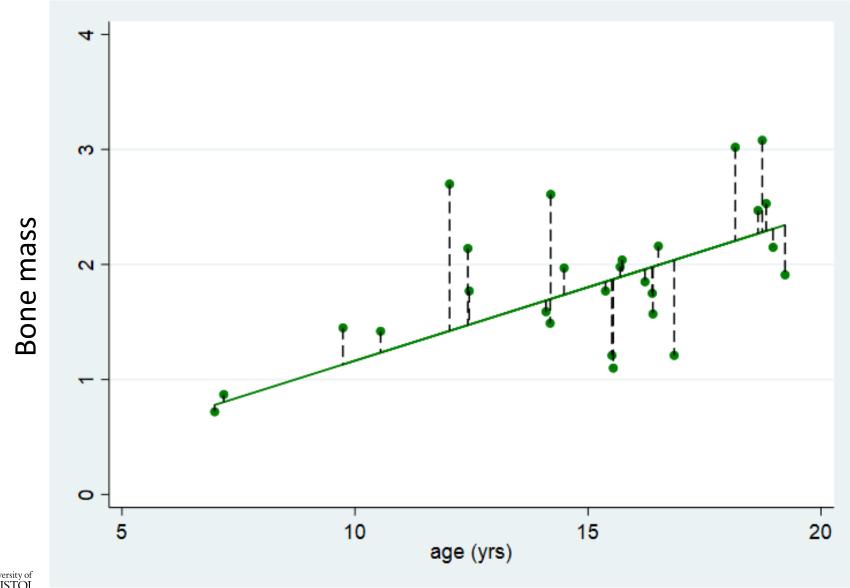








Adding a line of best fit

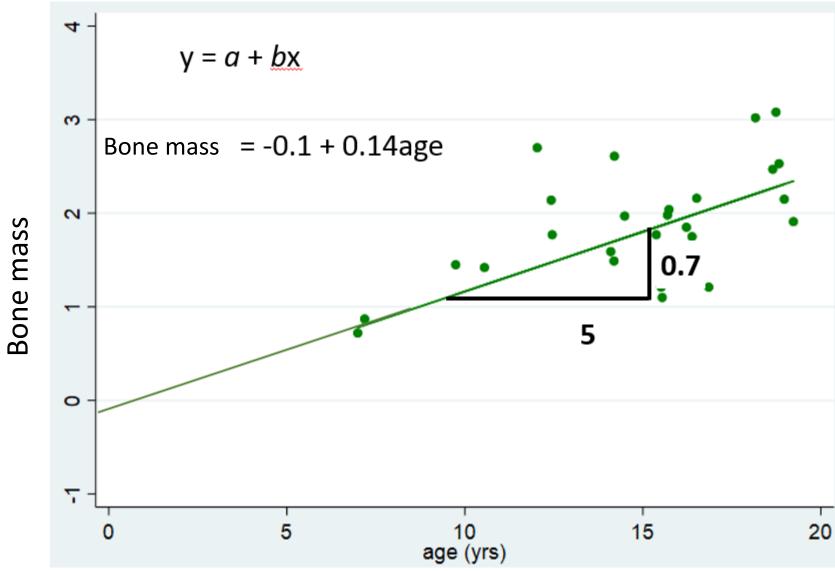








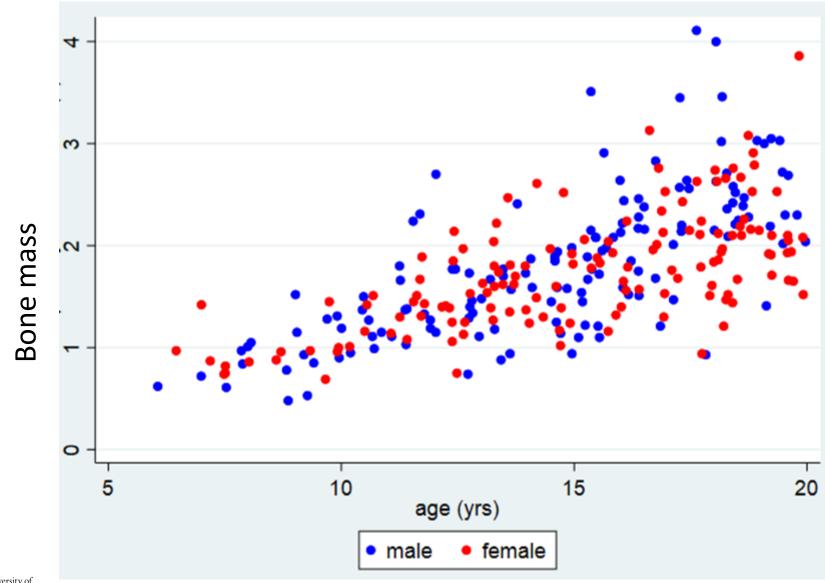
The intercept and the slope







Two populations within this distribution

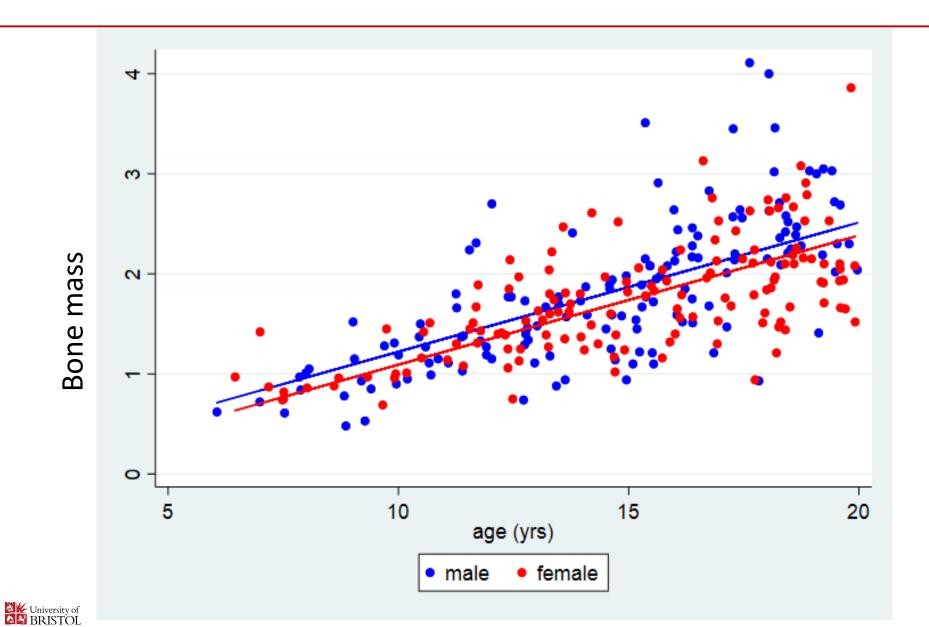








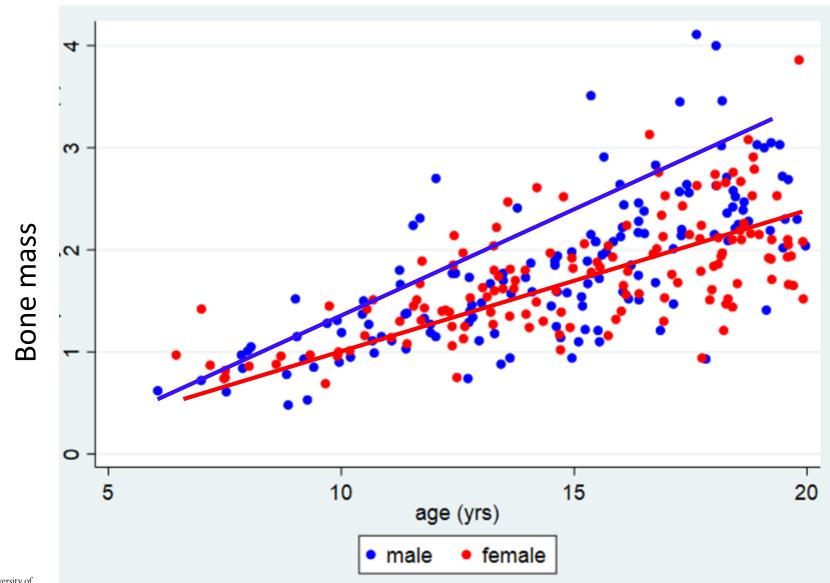
Each with lines of best fit with the same slopes







...or different slopes... This is interaction

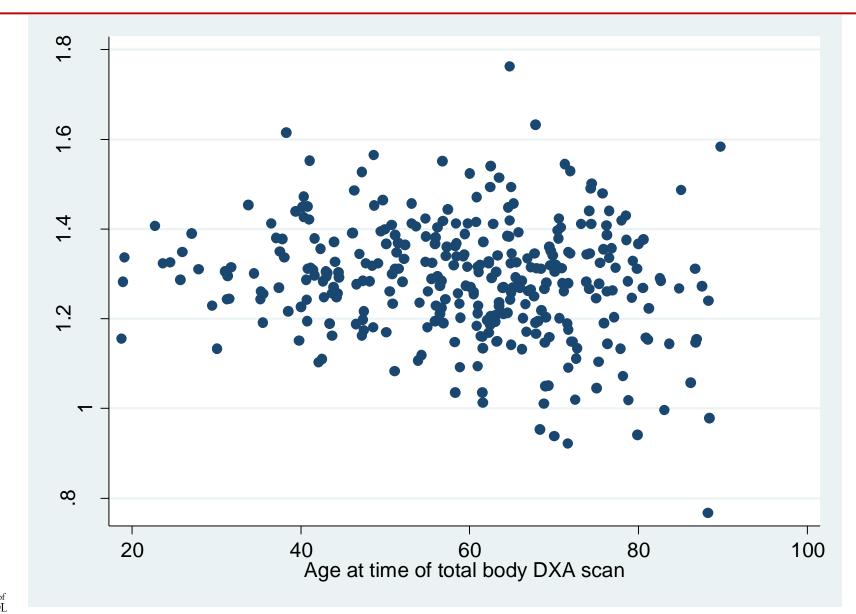








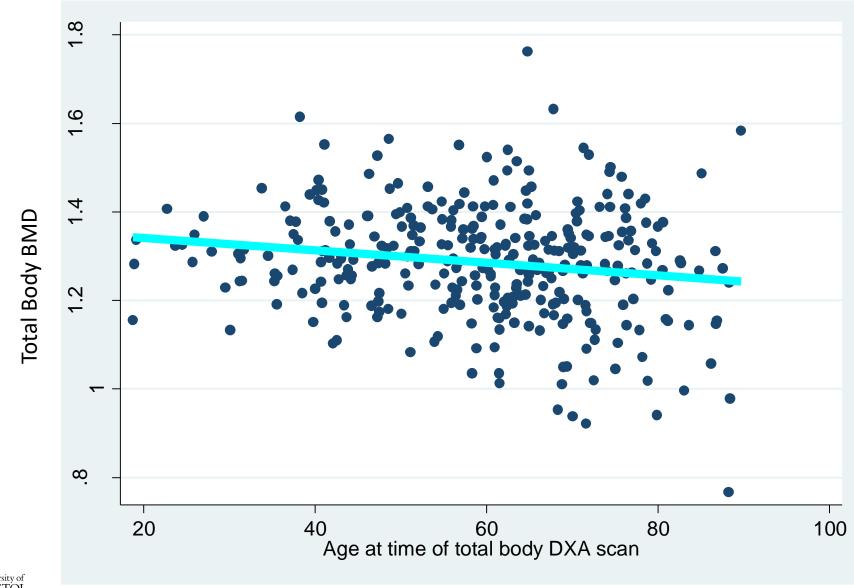
An example: Total Body BMD by Age







Adding in a regression line:









regress outcome exposure

reg tb bmd age

Source	SS	df	MS	Numbe	er of ob	s =	328
Model Residual	.145290357 5.24668332	1 326	.145290357 .016094121		> F	= = =	9.03 0.0029 0.0269
Total	5.39197368	327	.016489216	_	k-square MSE	d = =	0.0240 .12686
tb_bmd	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
age _cons	0014089 1.369698	.0004689		0.003 0.000	0023 1.313		0004864 1.426051



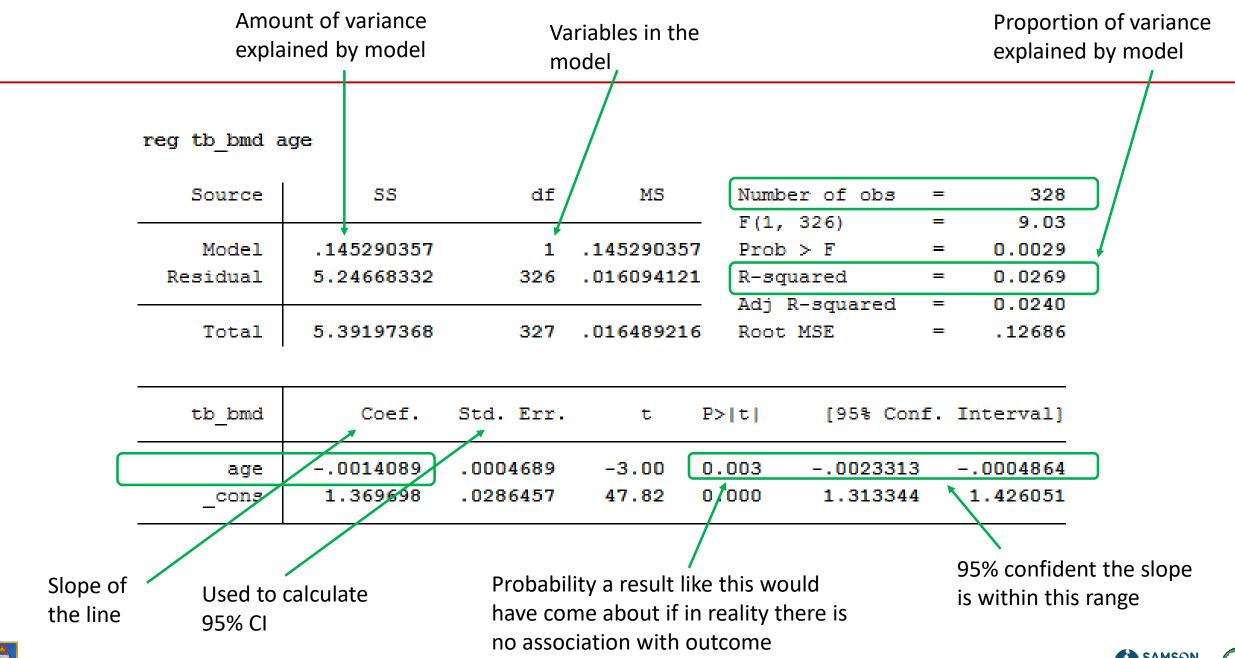


reg tb_bmd age

Source	SS	df	MS	Number of obs	=	328
-				F(1, 326)	=	9.03
Model	.145290357	1	.145290357	Prob > F	=	0.0029
Residual	5.24668332	326	.016094121	R-squared	=	0.0269
				Adj R-squared	. =	0.0240
Total	5.39197368	327	.016489216	Root MSE	=	.12686
tb_bmd	Coef.	Std. Err.	t I	?> t [95% C	onf.	Interval]
age	0014089	.0004689	-3.00 0	0.00300233	13	0004864
_cons	1.369698	.0286457	47.82	0.000 1.3133	44	1.426051



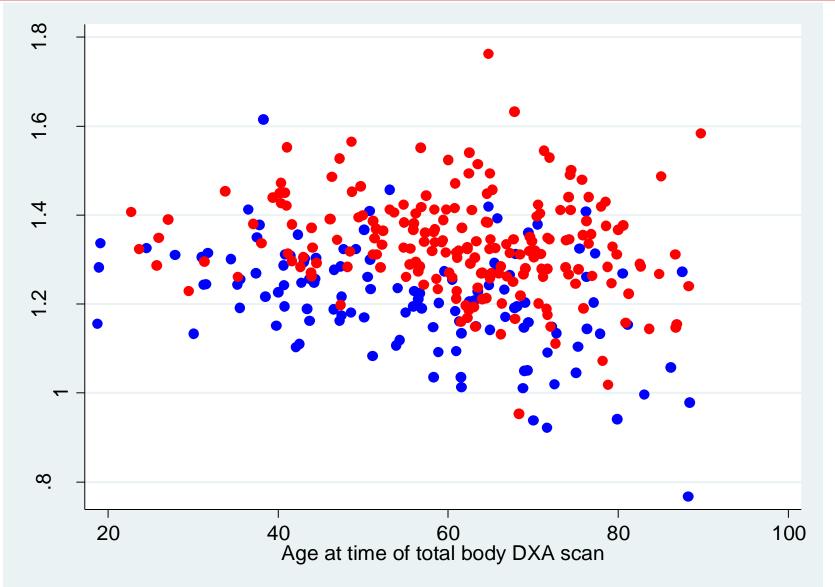








But there are 2 populations – with and without high bone mass



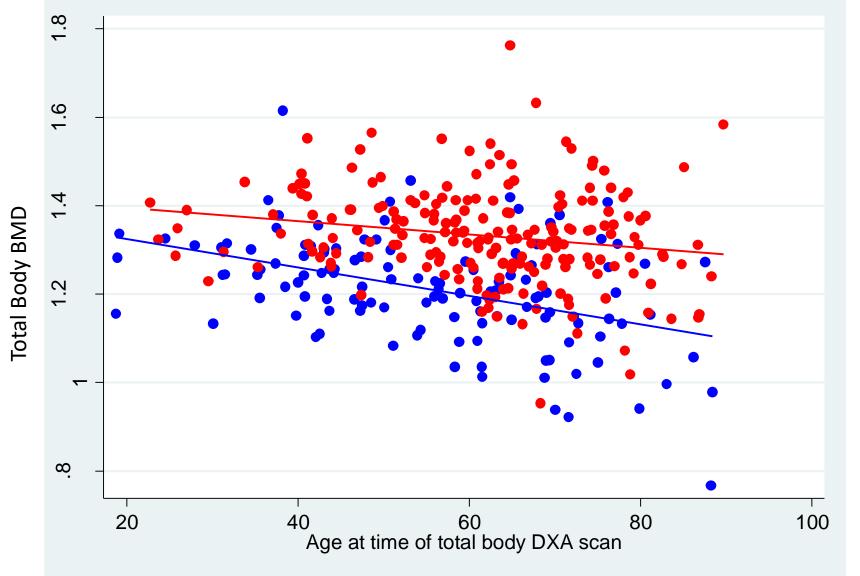
HBM cases in red Normal individuals in blue







Testing for interaction: Is the slope of the regression lines different?



HBM cases in red Normal individuals in blue

HBM 1 Non-HBM 0







Test for interaction: reg tb_bmd i.hbm##c.age

. reg tb bmd i.hbm##c.age

	_	3						
	Source	SS	df	MS	Numl	ber of obs	=	328
-					F(3	, 324)	=	44.37
	Model	1.57011575	3	.523371916	Prol	o > F	=	0.0000
	Residual	3.82185793	324	.011795858	R-s	quared	=	0.2912
-					Adj	R-squared	=	0.2846
	Total	5.39197368	327	.016489216	Root	t MSE	=	.10861
	'	•						
-	tb_bmd	Coef.	Std. Err.	t	P> t	[95% Co	onf.	Interval]
-								
	1.hbm	0368218	.0495197	-0.74	0.458	134242	25	.0605989
	age	0015079	.0005569	-2.71	0.007	002603	35	0004123
	hbm#c.age							
	1	0017025	.0008221	-2.07	0.039	003319	98	0000853
	cons	1.425571	.0351261	40.58	0.000	1.35646	57	1.494675
	_							





Test for interaction: reg tb bmd i.hbm##c.age

. reg tb bmd i.hbm##c.age Source SS df MS Number of obs 328 F(3, 324) 44.37 Model 1.57011575 Prob > F .523371916 0.0000 Residual 3.82185793 324 .011795858 R-squared 0.2912 Adj R-squared 0.2846 5.39197368 .016489216 Root MSE Total 327 .10861 tb bmd Coef. Std. Err. P>|t| [95% Conf. Interval] t 1.hbm -.0368218 .0495197 -0.740.458 -.1342425 .0605989 Slope of line for -.0015079 .0005569 -2.710.007 -.0026035 -.0004123 age baseline group hbm#c.age (non-HBM) -.0017025 .0008221 -2.070.039 -.0033198 -.0000853 _cons 1.425571 .0351261 40.58 0.000 1.356467 1.494675 Y axis intercept for baseline group

(non-HBM)







Test for interaction: reg tb bmd i.hbm##c.age

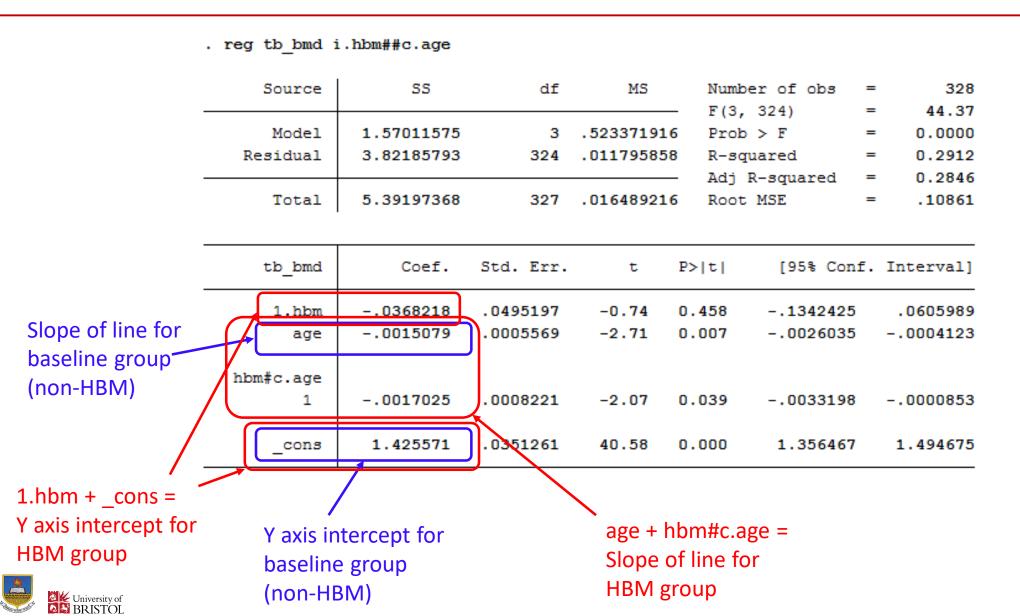
. reg tb bmd i.hbm##c.age Source SS df MS Number of obs 328 F(3, 324) 44.37 Mode1 1.57011575 Prob > F 0.0000 .523371916 Residual 3.82185793 324 .011795858 R-squared 0.2912 Adj R-squared 0.2846 5.39197368 .016489216 Root MSE Total 327 .10861 tb bmd Coef. Std. Err. P>|t| [95% Conf. Interval] 1.hbm -.0368218 .0495197 -0.740.458 -.1342425.0605989 Slope of line for -.0015079 .0005569 -2.710.007 -.0026035 -.0004123 age baseline group hbm#c.age (non-HBM) 0008221 -2.07-.0033198 -.0017025 0.039 -.0000853 _cons .0351261 1.425571 40.58 0.000 1.356467 1.494675 age + hbm#c.age = Y axis intercept for Slope of line for baseline group HBM group (non-HBM)







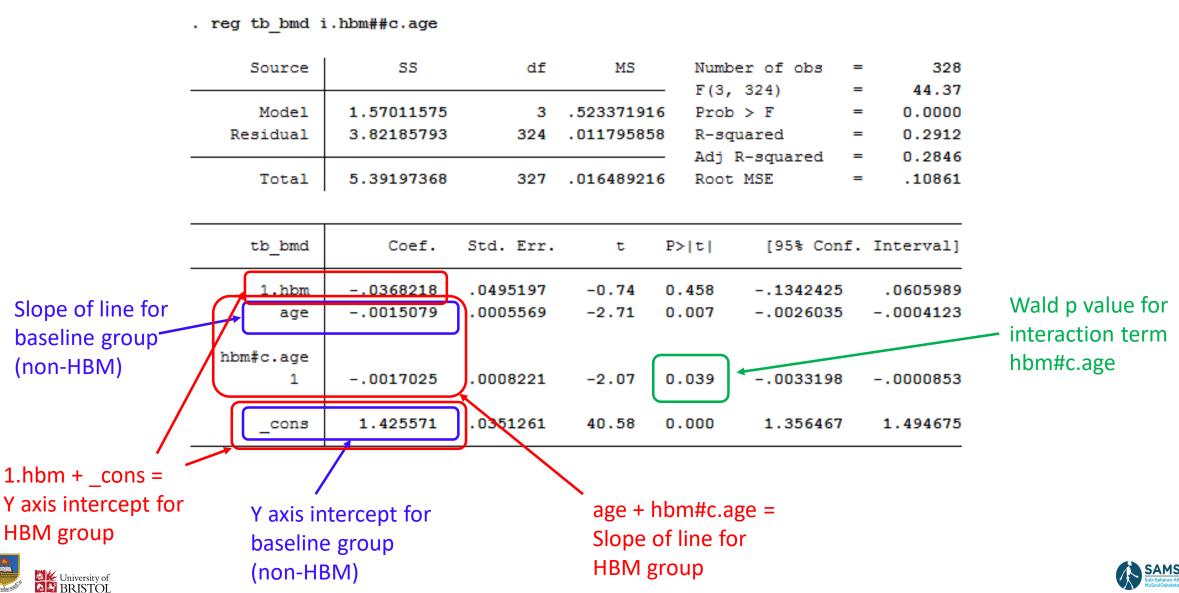
Test for interaction: reg tb_bmd i.hbm##c.age







Test for interaction: reg tb bmd i.hbm##c.age







Post regression command: lincom

```
age + hbm#c.age =
. lincom age + 1.hbm#c.age
                                    Slope of line for
(1) age + 1.hbm#c.age = 0
                                    HBM group
```

tb_bmd	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
(1)	0032104	.0006047	-5.31	0.000	0044	0020208

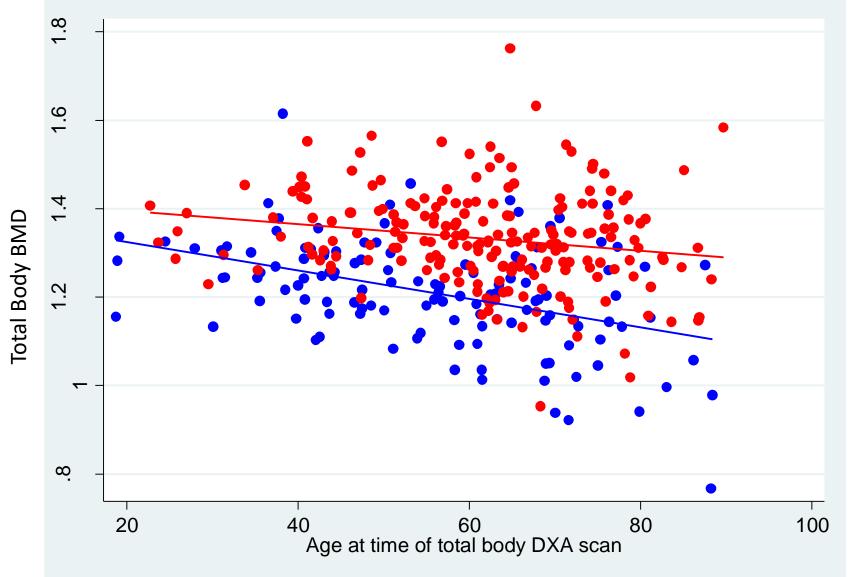
. lincom _cons + 1.hbm	1.hbm + _cons =		
	Y axis intercept for		
(1) 1.hbm + _cons = 0	HBM group		

tb_bmd	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
(1)	1.388749	.034905	39.79	0.000	1.32008	1.457418





Testing for interaction: Is the slope of the regression lines different? – Yes!



HBM cases in red Normal individuals in blue

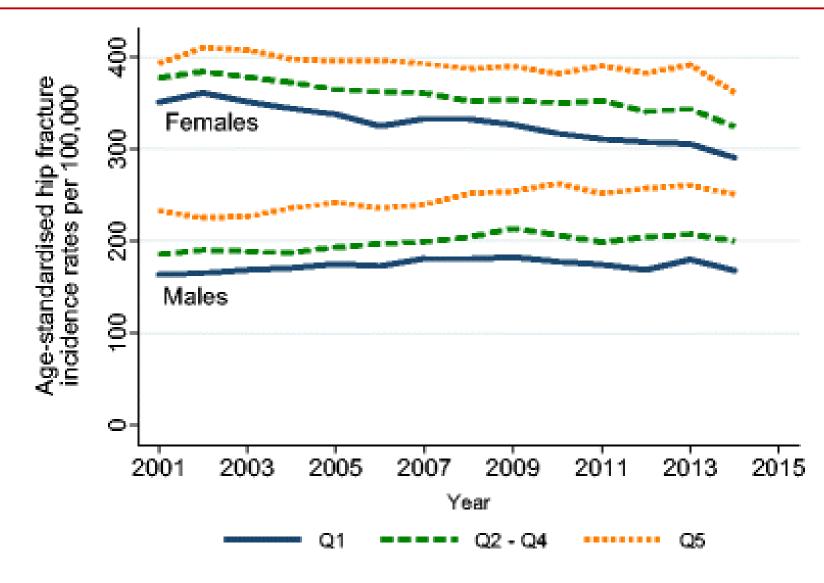
HBM 1 Non-HBM 0







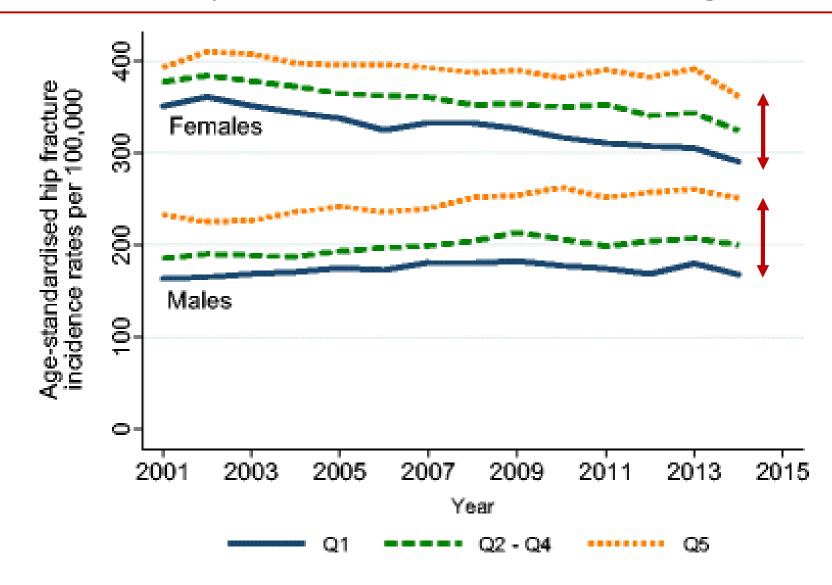
Another example: The effect of social deprivation (quintiles) on hip fracture incidence in England







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- Interaction is an *important property* of the relationship between two factors, and their influence on an outcome
- You do not try to eliminate this effect, instead you want to detect and describe interaction in the greatest possible detail
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