

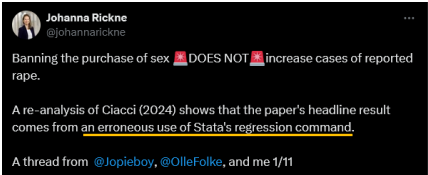
announcements

- Problem Set 8 is due today
- Drill will be happening this week ... maybe
- Next Monday is a day off
- Problem Set 7's answer key is done, but grading is not



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sometimes data analysts make mistakes



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mediation analysis: wrap-up

April 1, 2024

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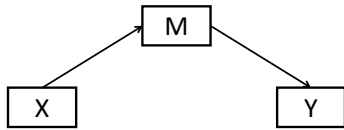
thinking about mediation

complexities of third-variable control & other considerations

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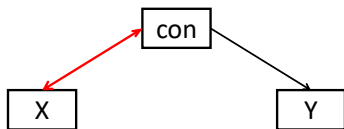
mediation: what we think is happening

- if one variable influences another through an intervening variable, the intervening variable is typically called a *mediator*



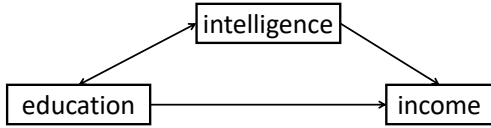
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confounds: equivalent mathematically



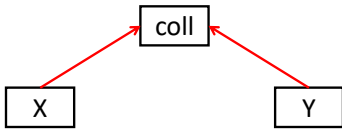
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an example of a (probable?)
confound



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colliders:
similar mathematically



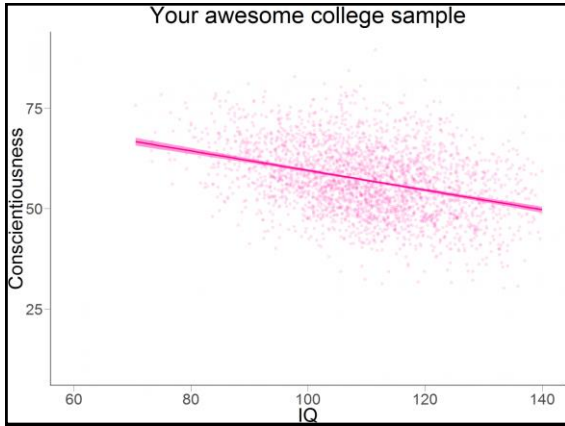
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an example of collider bias

- imagine you are interested in the relationship between intelligence (indexed by IQ) and conscientiousness
- you find a large sample of college students and find ...
 $r = -.37$
- what?!

<http://www.the100.c/2017/03/14/that-one-weird-third-variable-problem-nobody-ever-mentions-conditioning-on-a-collider/>

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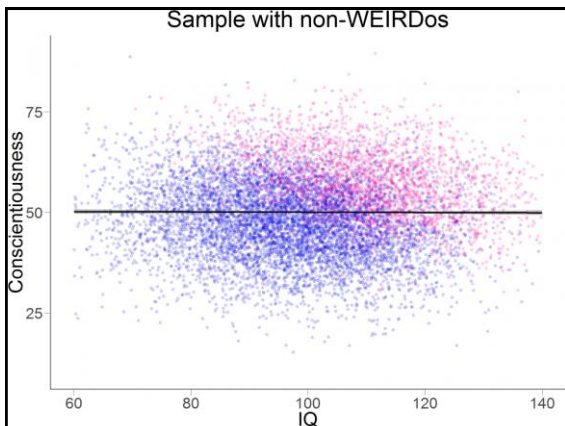


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what's going on?

- college students tend to be higher IQ than the general population; they also tend to be higher with respect to conscientiousness
- that is, both of these variables are predictors of college-student membership; they "collide"
- so selecting from the college-student population "conditions on a collider", creating a (strange) relationship that doesn't exist in the whole population

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third-variable patterns (problems?), cataloged, probably not completely

- confounds
- colliders
- suppressors
- mediators
- covariates

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2819361/>
<https://www.ncbi.nlm.nih.gov/pubmed/28575894>

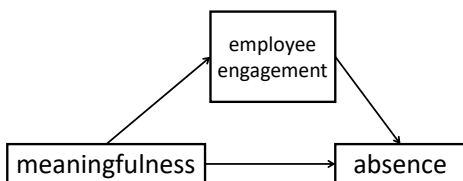
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mediation extensions

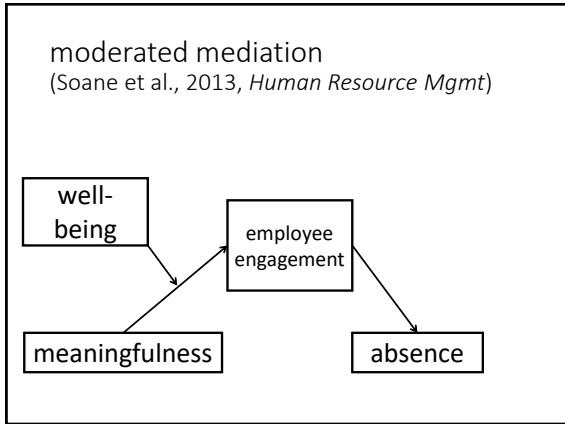
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moderated mediation

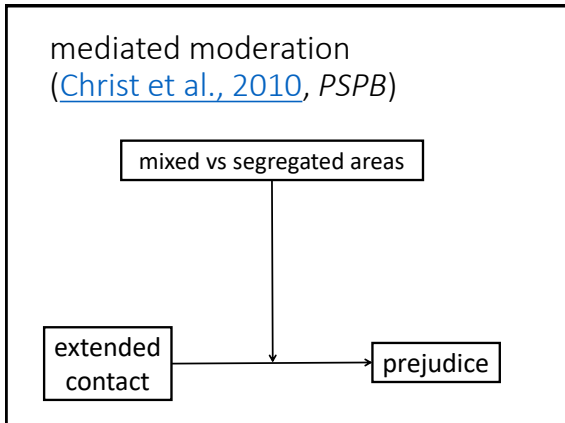
([Soane et al., 2013](#), *Human Resource Mgmt*)



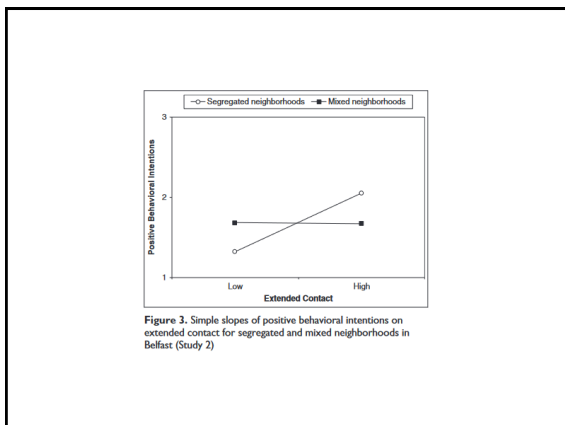
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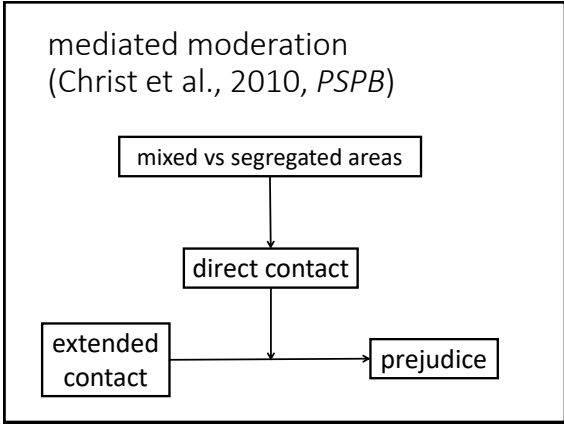
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non-independence in data

introduction to non-independence,
its consequences,
and repeated-measures designs

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assumptions made in modeling

- these are about residuals! (not about predictors)

1. they're normally distributed
2. they have constant variance (homoscedasticity)
3. they are independent of one another

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independence?

- independence means that any one individual's residual **can't** be used to estimate another's
- when is this violated?
- usually it's a *feature* of the research design
- common situations
 - repeated-measures studies
 - longitudinal studies
 - naturally-clustered data (e.g., students in classrooms)
 - research with dyads or group interactions

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types of nonindependence

- positive nonindependence
- scores (residuals) are positively related
- negative nonindependence
- scores (residuals) are negatively related

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positive nonindependence (an example)

- if we ask couples to rate satisfaction with their relationship, we'd likely see high scores paired with high scores and low scores with low scores
- one person's score predicts the other's

couple	partner 1	partner 2
a	1	1
b	4	3
c	6	7
d	5	6

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negative nonindependence (an example)

- if we ask couples to estimate how much housework each person does, we'd likely see high scores paired with low scores and vice versa
- one person's score predicts the other's

couple	partner 1	partner 2
a	30%	80%
b	40%	75%
c	70%	40%
d	20%	100%

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consequences of nonindependence

- this depends on the type (positive or negative)
- and on how nonindependence fits within the design
- it can in some circumstances increase Type I errors, and in others it can increase Type II errors

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