Multiple Regression Models	<ul> <li>Advantages of Multiple Regression</li> <li>Practical issues</li> <li>better prediction from multiple predictors</li> <li>can "avoid" picking/depending on a single predictor</li> <li>can "avoid" non-optimal combinations of predictors (e.g., total scores)</li> </ul>
<ul> <li>Advantages of multiple regression</li> <li>Important preliminary analyses</li> <li>Parts of a multiple regression model &amp; interpretation</li> <li>Raw score vs. Standardized models</li> <li>Differences between r, b<sub>biv</sub>, b<sub>mult</sub> &amp; β<sub>mult</sub></li> <li>Steps in examining &amp; interpreting a full regression model</li> <li>Underspecification &amp; Proxy Variables</li> <li>Searching for "the model"</li> </ul>	<ul> <li>Theoretical issues</li> <li>even when we know in our hearts that the design will not support causal interpretation of the results, we have thoughts and theories of the causal relationships between the predictors and the criterion and these thoughts are about multicausal relationships</li> <li>multiple regression models allow the examination of more sophisticated research hypotheses than is possible using simple correlations</li> <li>gives a "link" among the various correlation and ANOVA models</li> </ul>
<ul> <li>Before launching into the various hypotheses tests and other types of analyses, be sure to "get familiar" with your data and determine if it has any "problems" …</li> <li>1. Perform appropriate data checking &amp; cleaning <ul> <li>non-normality, outliers &amp; nonlinearities?</li> </ul> </li> <li>2. Get means and standard deviations for each variable <ul> <li>do they "make sense" for these measures &amp; this population?</li> </ul> </li> <li>3. Consider the correlations of each variable with the criterion <ul> <li>do they "make sense" for these measures &amp; this population?</li> </ul> </li> </ul>	
<ul> <li>4. Consider the correlations among the predictors (collinearities)</li> <li>• do they make sense for these measures &amp; this population?</li> <li>• will there be a "collinearity problem" ?</li> </ul>	

raw score regression

 $y' = b_1 x_1 + b_2 x_2 + b_3 x_3 + a$ 

each b

- represents the unique and independent contribution of that predictor to the model
- for a quantitative predictor tells the expected direction and amount of change in the criterion for a 1-unit change in that predictor, while holding the value of all the other predictors constant
- for a binary predictor (with unit coding -- 0,1 or 1,2, etc.), tells direction and amount of group mean difference on the criterion variable, while holding the value of all the other predictors constant

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• the expected value of the criterion if all predictors have a value of 0

Let's practice -- Tx (0 = control, 1 = treatment)

depression' = (2.0 \* stress) - (1.5 \* support) - (3.0 \* Tx) + 35

- interpret "a" -- if a person has a score of "0" on all predictors, their depression is expected to be  $\ 35$
- apply the formula patient has stress score of 10, support score of 4 and was in the treatment group dep' = 46
- interpret "b" for stress -- for each 1-unit increase in stress, depression is expected to increase by 2 , when holding all other variables constant
- $\bullet$  interpret "b" for support -- for each 1-unit increase in support, depression is expected to decrease by  $_{1.5}$  , when holding all other variables constant

• interpret "b" for tx – those in the Tx group are expected to have a mean depression score that is 3.0 lower than the control group, when holding all other variables constant

standard score regression  $Z_y' = \beta Z_{x1} + \beta Z_{x2} + \beta Z_{x3}$ 

# $\text{each }\beta$

- for a quantitative predictor the expected Z-score change in the criterion for a 1-Z-unit change in that predictor, holding the values of all the other predictors constant
- for a binary predictor, tells size/direction of group mean difference on criterion variable in Z-units, holding all other variable values constant

As for the standardized bivariate regression model there is no "a" or "constant" because the mean of Zy' always = Zy = 0

The most common reason to refer to standardized weights is when you (or the reader) is unfamiliar with the scale of the criterion. A second reason is to promote comparability of the relative contribution of the various predictors (but see the important caveat to this discussed below!!!).



It is important to discriminate among the information obtained from ...

bivariate r & bivariate regression model weights

r -- simple correlation

tells the direction and strength of the linear relationship between two variables (r =  $\beta$  for bivariate models)

r<sup>2</sup> -- squared correlation

tells how much of the Y variability is "accounted for," "predicted from" or "caused by" X ( $r = \beta$  for bivariate models)

b -- raw regression weight from a bivariate model

tells the expected change (direction and amount) in the criterion for a 1-unit change in the predictor

 $\beta$  -- standardized regression wt. from a bivariate model

tells the expected change (direction and amount) in the criterion in Z-score units for a 1-Z-score unit change in that predictor, holding the value of all the other predictors constant It is important to discriminate among the information obtained from ...

multivariate R & multivariate regression model weights

- R<sup>2</sup> -- squared multiple correlation tells how much of the Y variability is "accounted for,"
  . "predicted from" or "caused by" the multiple regression model
- R -- multiple correlation (not used that often) tells the strength of the relationship between Y and the multiple regression model
- b<sub>i</sub> -- raw regression weight from a multivariate model

tells the expected change (direction and amount) in the criterion for a 1-unit change in that predictor, holding the value of all the other predictors constant

 $\beta_i$  -- standardized regression wt. from a multivariate model

tells the expected change (direction and amount) in the criterion in Z-score units for a 1-Z-score unit change in that predictor, holding the value of all the other predictors constant





Remember that the b of each predictor represents the part of that predictor shared with the criterion that is not shared with any other predictor -- the unique contribution of that predictor to the model



Remember R<sup>2</sup> is the total variance shared between the model (all of the predictors) and the criterion (not just the accumulation of the parts uniquely attributable to each predictor).



Inspecting and describing the results of a multiple regression formula ...

- 0. Carefully check the bivariate correlations/regressions
- 1. Does the model work?

F-test (ANOVA) of H0:  $R^2 = 0$  (R=0)

 $(R^{2}) / k \qquad k = \# \text{ preds of in the model}$   $F = \frac{(R^{2}) / (N - k - 1)}{(1 - R^{2}) / (N - k - 1)} \qquad F = \text{total number of subjects}$ Find F-critical using df = k N-k-1

2. How well does the model work?

• R<sup>2</sup> is an "effect size estimate" telling the proportion of variance of the criterion variable that is accounted for by the model

• adjusted R<sup>2</sup> is an attempt to correct R<sup>2</sup> for the inflation possible when the number if predictors is large relative to the sample size (gets "mixed reviews" -- replication is better!!)

- 3. Which variables contribute to the model ??
  - t-test of H0: b = 0 for *each variable*

Rember: b tells the contribution of this predictor to this model

- 4. Which variables contribute "most" to the model
  - **careful** comparison of the predictor's  $\beta$ s
  - don't compare predictor's bs more about why later!
  - A related question is whether one or more variables can be "dropped" from the model
- 5. Identify the difference between the "bivariate story" and the "multivariate story"
  - Compare each multivariate b/ $\beta$  with the corresponding bivariate r and/or bivariate b/ $\beta$

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• Bivariate & different multivariate "stories" may differ

What's the problem with under-/misspecification .. cont ???

Since our model will tend to have fewer predictors than the complete model, predictors in the model are not competing with all the predictors that should be in model...

• the amount of collinearity is less than it would be in the full model

the "collinearity mix" is different than it would be in the full model
weights are trying to "make up for" predictors not in the model

#### So ...

- the resulting b weights will tend to overestimate the unique contribution of each predictor (increasing Type I errors)
- the resulting b weights might underestimate the unique contribution of each predictor (increasing Type II errors)
- the resulting b weights might have the wrong sign and misrepresent the unique contribution of a predictor (increasing Type III errors)

Model Specification & why it matters !!!

What we need to remember is that we will never, ever (even once) have a "properly specified" multiple regression model  $\rightarrow$  one that includes all of & only the causal variables influencing the criterion !

Thus our model is – misspecified – including only some of the causal variables influencing the criterion (underspecification) and maybe has variables that don't influence the (flooded).

What's the problem with misspecification?

- Remember that each b  $(\beta)$  weight tells the direction and extent of the contribution of that variable to that model controlling for all the other variables in that model
- So, if we don't have a properly specified model, the regression weights for the variables that are in the model don't necessarily tell us what we hope to learn

• Said differently – the "unique contribution" of a particular predictor might vary importantly, depending up on what other predictors have been included in the model

What's the problem with underspecification .. some more ???

Since our model will tend to have fewer predictors than the complete model ...

The  $R^2$  is "smaller than it should be" and the error variance  $(1-R^2)$  is "larger than it should be"

• Since this error term is used in the model F-test and each of the multiple regression weight t-tests, all of those tests tend toward "missing" effects (Type II error)

#### Summary idea ...

Behavior is complicated, and so, larger models are, on average, more accurate! When predictors are added (on average) ...

- R<sup>2</sup> goes up and error terms go down reducing Type II errors
- The amount of collinearity increases limiting Type I errors
- The collinearity mix is more correct limiting Type III errors

What can we do about "misspecification" ?

- running larger models with every available predictor in them won't help models with many predictors tend to get really messy
- our best hope is to base our regression models upon the existing literature & good theory and to apply programmatic research
  - include variables that are known to be related to that criterion - will help avoid Type I errors from a poor collinearity mix
  - include only "other variables" that there are theoretical reasons to think may contribute to the model
  - use the largest and most representative samples available
  - run multiple models identify those variables that have consistent contribution (or not) across models with different subsets of predictors
  - replicate a lot!



### Proxy variables

Remember (again) we are not going to have experimental data!

The variables we have might be the actual causal variables influencing this criterion, or (more likely) they might only be correlates of those causal variables – proxy variables

Again, replication and especially convergence (trying alternative measure of the involved constructs) can help decide if our predictors are representing what we think the do!!

This is also why we will look at "path analysis" and "mediation analyses"!! These are important variations of multiple regression that allow us to look at "what comes in-between" the "causes" and the "effects" and can often help us better interpret the complex associations we reveal using multiple regression!

### Proxy variables

In sense, proxy variables are a kind of "confounds"  $\rightarrow$  because we are attributing an effect to one variable when it might be due to another.

We can take a similar effect to understanding proxys that we do to understanding confounds  $\rightarrow$  we have to rule out specific alternative explanations !!!

An example r<sub>attendance, performance</sub> = .4 Is it really attendance?

Motivation, amount of preparation & testing comfort are some variables that are related to both attendance and performance.

So, we run a multiple regression with all four as predictors.

If attendance doesn't contribute, then it "really wasn't" attendance but the other variables.

If attendance contributes to that model, then we know that "attendance" in the model is "the part of attendance that isn't motivation, preparation or comfort" and we can start to figure out what that is....

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### Searching for "the model" with multiple regression

There are four things that routinely thwart our attempts to find "the model"

- 1. Collinearity because of the correlations among the predictors (which are sometimes stronger than the predictors are correlated with the criterion) there are often alternative models that perform equally well
- 2. Underspecification there's just no way we can ever test that "no other predictor" would contribute (one solution is to decide theoretically on the set of predictors - almost cheating)
- 3. Also, again because of collinearity, it is possible to include a variable in model that, while it doesn't contribute to the model, does change the size or even the sign of other predictors in the model. If so, the more "parsimonious" model might not be the most accurate.
- 4. Sampling variability ... as always

## Searching for "the model" with multiple regression

- A common question is," What is the best multiple regression model for this criterion?"
- This certainly seems like an important question, because such a model would tell us what variables must be considered to predict or perhaps understand the criterion & what variables can be safely ignored in our theory and practice.
- A "the model" would have three important properties...
- 1. Every predictor in the model contributes to the model (parsimony or necessity)
- 2. No other predictor would contribute to the model if it were added (sufficiency)
- 3. No other predictor, if added to the model, would change the "structure" of the model (i.e., regression weights of the other predictors in the model)

So, what are we to do?

Rather than telling "the model" we need to tell "the story" (which also gives us the best chance of finding the model if it is out there...)

"the story" is told from ...

- 1. Each predictor's correlation with the criterion and the collinearities among predictors
- 2. Each predictor's contribution to the full model (noting likely reasons why variables don't contribute and suppressors)
- 3. Relative utility (R<sup>2</sup>) of alternative models and each predictor's contribution to each
- 4. Building a story of which predictors contribute to what model(s) when included in them

So, what are we to do? No really ?????

- Concerns about underspecification, proxy's and modeling are all well and good, but we have to actually "get a model" once in a while!!
- Much as we fret about and include in the discussion sections of our article an admission of the "procedural" limitations of our research, we need to fret about and admit to the measurement & modeling limitations of our research.
- This is another example of the importance of replication and convergence via programmatic research!
- So, remember & worry about these things, but don't let that worry be debilitating!
- Work with the best variables & data you can get, test hypotheses (even mid-hoc ones) whenever possible, propose & test models and their alternatives, etc.