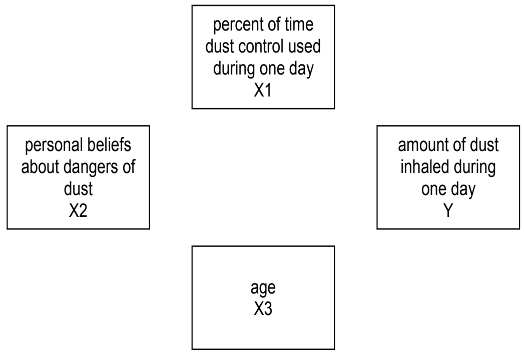
Slide 1

A team of occupational health researchers is interested in decreasing the amount of dust inhaled by wood shop employees in Minnesota. They have found that there is large variability across employees in the amount of dust they inhale. Because the researchers are ultimately interested in some sort of intervention or change in policy, they want to build a causal model to explain what is causing individuals to have different levels of dust inhalation. In a study of a total of 100 employees at 10 different shops (10 employees from each shop) the following four variables were collected:

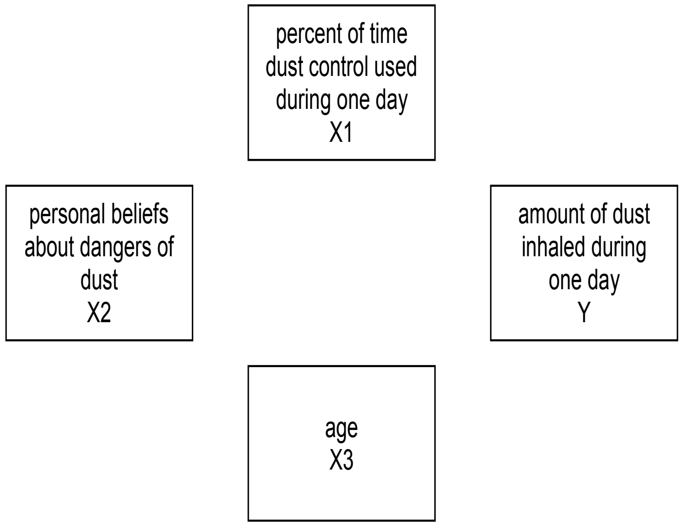


where X1 was observed for each employee by the occupational health researchers on the set study day and Y was measured using a dust monitoring device worn around the neck of each employee on the set study day. X2 and X3 were self-report measures by each employee with X2 being the sum of 4 Likert items with higher values indicating a strong belief that dust is dangerous. All simple correlations between these four variables based on the report of the 100 employees are statistically significant.

Slide 2

1. Construct a causal path model which could reasonably explain how the three variables X1, X2, and X3 cause Y. For every variable that you make an outcome in your model make sure to attach an error. Also, give labels to all your direct paths, e.g. β_1, β_2, etc. (Note: Answers may vary)
2. Give a justification for your model (based on your understanding of the subject matter). That is, give an explanation for each direct path you drew and each you did not draw (i.e. if you do not draw a direct relationship between two variables you should explain why not).
3. Based on your model
   (a) Does X1 have any indirect effect on Y, if so what is its value in terms of β's
   (b) Does X2 have any indirect effect on Y, if so what is its value in terms of β's
   (c) Does X3 have any indirect effect on Y, if so what is its value in terms of β's
4. Pick any one of the direct paths you drew and give an interpretation of its associated β.
5. Assume you knew that the quality of the air ventilation system at the different shops varied, and that this variable (which wasn't measured) has a direct causal influence on how much dust is inhaled by employees in the different shops. Does not including this variable in the model bias the effect estimates in your model? Why or why not.

Slide 3



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Slide 4

Slide 5

To include W or not to include W

Our interest is in estimating the total causal effect of X on Y, i.e. $X \to Y$

In certain situations, the causal effect is estimated by $\hat{\beta}$ obtained from fitting the simple regression equation

$$Y = \beta X + \epsilon$$

and in some other situations, the causal effect is estimated by $\hat{\beta}_1$ obtained from fitting the regression equation including variables W

$$Y = \beta_1 X + \beta_2 W + \epsilon$$

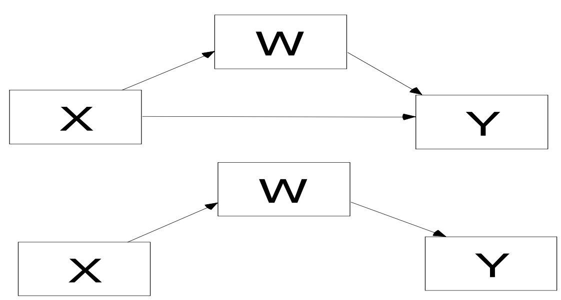
The question is, when does W need to be included or not.....

Slide 6

To include W or not to include W

Our interest is in estimating the total causal effect of X on Y, i.e. $X \to Y$

If there is a variable W such that one of the following models is true



It is **not necessary** to include W in the model in order to unbiasedly estimate the total causal effect of X on Y.

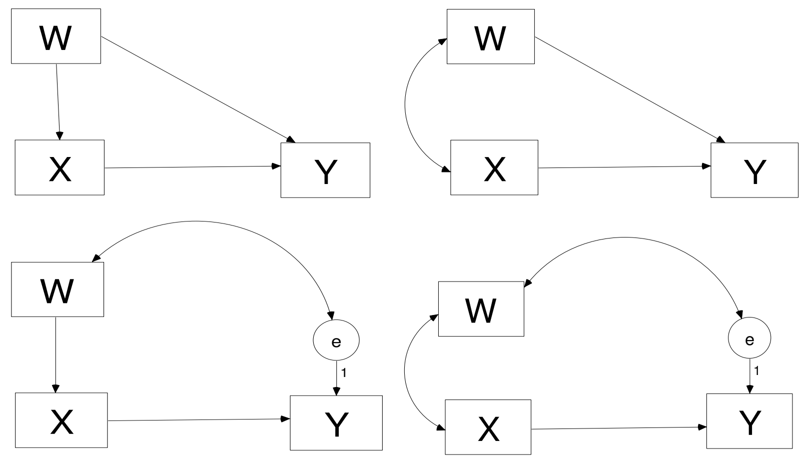
Note that if W is included, the direct causal effect of X on Y will be different than if W wasn't included. But the same total causal effect will arise with or without W. That is, when W is included the total causal effect equals the direct plus indirect causal effects.

Slide 7

To include W or not to include W

Our interest is in estimating the total causal effect of X on Y, i.e. $X \rightarrow Y$

The variable W is a **confounder** in each of the following models



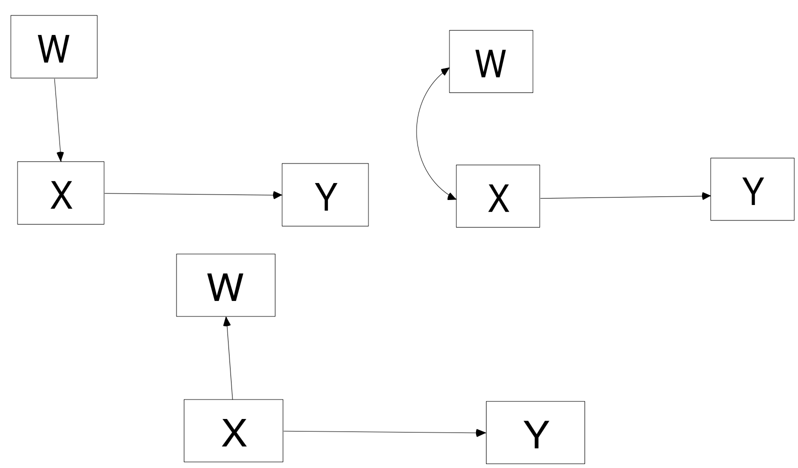
Then W **must** be included in the model in order to unbiasedly estimate the causal effect that X has on Y.

Slide 8

To include W or not to include W

Our interest is in estimating the total causal effect of X on Y, i.e. $X \rightarrow Y$

If there is a W such that one of the following models is true



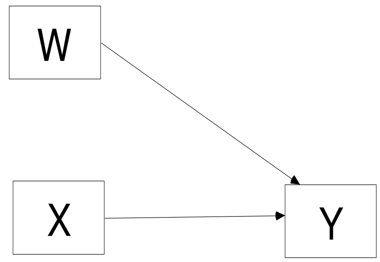
In each case the partial correlation between Y and W is zero once X is taken into account, thus there will be **no difference** whether W is included or not

Slide 9

To include W or not to include W

Our interest is in estimating the total causal effect of X on Y, i.e. $X \to Y$

If there is a W such that the following models is true



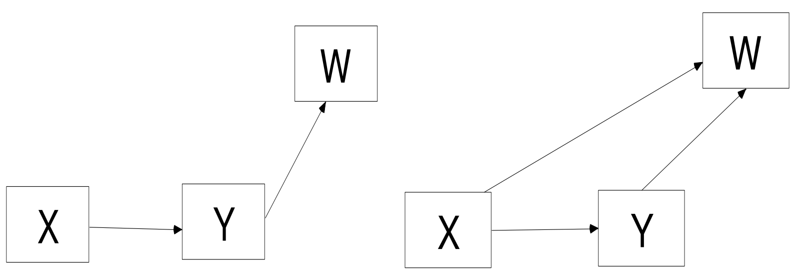
In this case the simple correlation between X and W is zero thus the estimate of the causal effect of X on Y is the **same** whether W is included or not. Note, the overall R^2 would be higher if W was included but again it would not effect the causal effect of X on Y.

Slide 10

To include W or not to include W

Our interest is in estimating the total causal effect of X on Y, i.e. $X \to Y$

If there is a W such that one of the following models is true



In these cases where W is caused by Y, W **should not be included** in the regression of Y on X in order to estimate the total causal effect of X on Y. Including W would result in biased estimates.

Moderator effects

- Same idea as an interaction effect.
- Does the relationship between variables differ across groups, if so then the group moderates the relationship.
- Can be examined using multiple group analysis. 6.10 of Kline.
- Perform chi-square test with direct paths constrained to be the same across the different groups, the perform chi-square allowing paths to be different. Then perform the chi-square difference test.

Slide 11

MEDIATORS AND MODERATORS IN THE EVALUATION OF PROGRAMS FOR CHILDREN

Current Practice and Agenda for Improvement

ANTHONY PETROSINO
American Academy of Arts & Sciences

Slide 12

Evaluation deals with the scientific assessment of the strengths and weaknesses of programs, policies, personnel, products, and organizations to improve their effectiveness.[1] Some of these assessments are outcome or impact evaluations. The evaluator in such studies focuses on the relationship of two variables: the independent variable representing the program and the dependent variable representing the outcome measure. In some studies,

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EVALUATION REVIEW, Vol. 24 No. 1, February 2000 47-72

Slide 13

Though mediator and moderator are terms often confused in practice (Baron and Kenny 1986), they represent distinct variables in an evaluation design. A mediator essentially serves as a causal link between a program and an effect (Mark, Hofmann, and Reichardt 1992). Baron and Kenny (1986) define a mediating variable as "the generative mechanism through which the focal independent variable is able to influence the dependent variable of interest" (p. 1173). In statistical terms, the mediator y is the consequence of the independent variable x but the antecedent of the dependent variable z (i.e., $x \rightarrow y \rightarrow z$). The attention to testing program theory in evaluation—particularly the underlying causal assumptions about why intervention should work—has emphasized the role of mediators in outcome studies (Weiss 1997).

In contrast to the causal relationship of the mediator to both the independent and dependent variable, moderators in an evaluation examine the interaction of the program variable with some other variable. In the treatment literature, moderator analyses are described as the search for differential or subgroup effects (Wilson 1980). Statistically, the variable y is a moderator if the relationship between the independent variable x and the dependent variable z varies as a function of y (i.e., the independent variable's effects vary along levels of the moderator; Mark, Hofmann, and Reichardt 1992).

Slide 14

A number of reviewers in various treatment areas recommend that future studies attend more to identifying and testing mediating and moderating effects, both in evaluations (Donaldson forthcoming) and meta-analyses (Petrosino 1998; Hall et al. 1994; Shadish and Sweeney 1991). Researchers recognize that intervention rarely has direct effects to reach program goals but works indirectly through one or more mechanisms (Donaldson forthcoming; Lipsey 1997). Intervention also rarely has the same across-the-board effects but often works for some persons in some settings at least some of the time (Wilson 1980). Some criticisms of evaluation largely comprising black-box interventions that analyze programs as undifferentiated wholes

can be addressed by effective use of mediating and moderating variables (Lipsey and Wilson, 1993).

Slide 15

Path Analysis

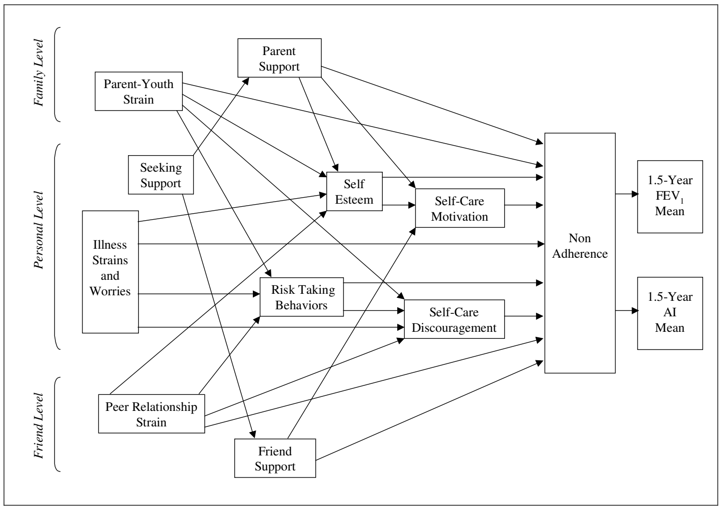
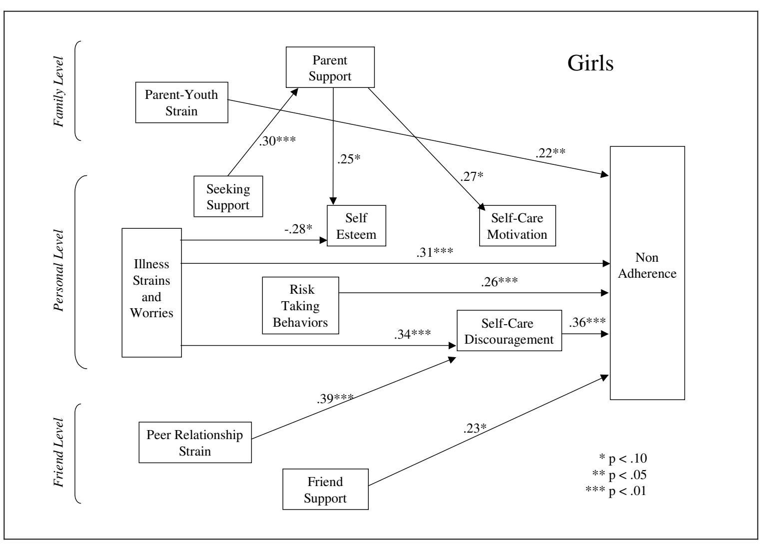


Figure 1. Conceptual model showing relationship between strains, resources, non-adherence feelings/behaviors and health outcomes for youth with CF

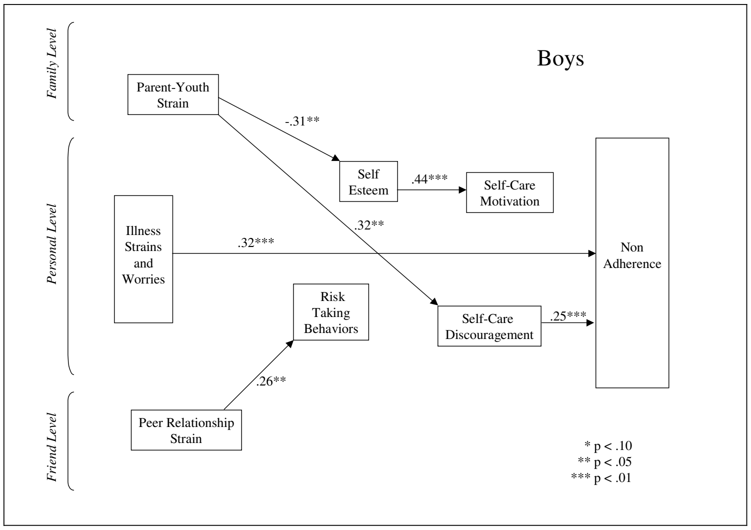
Slide 16

Gender as a moderator - multiple group analysis



Slide 17

Gender as a moderator - multiple group anlaysis

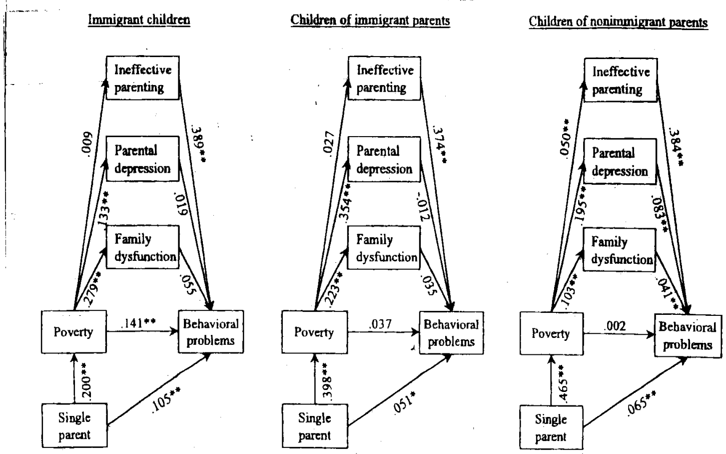


Slide 18

Multiple group chi-square difference test

Slide 19

FIGURE 1—Mediational pathways through which poverty affects children's emotional problems.

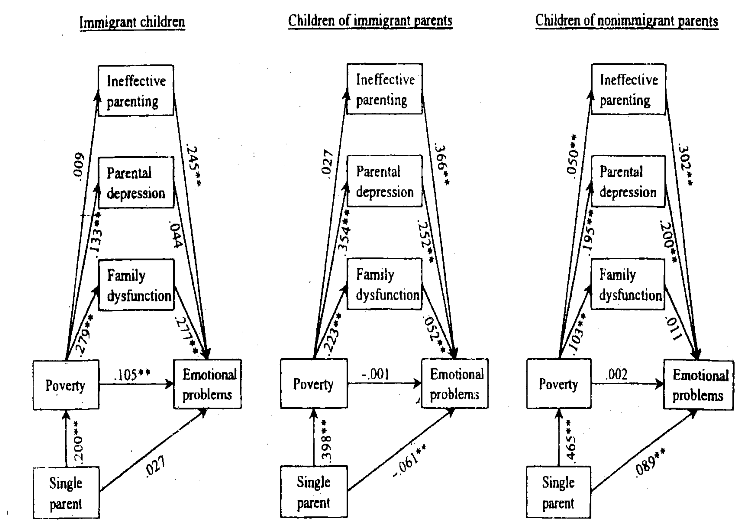


Note. Numbers are standard regression coefficients.
*P<.05; **P<.01.

FIGURE 2—Mediational pathways through which poverty affects children's behavioral problems.

The relation between poverty and behavioral problems is moderated by immigrant status.

Slide 20



Note. Numbers are standard regression coefficients.
*P<.05; **P<.01.