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Introduction to Structural Equations

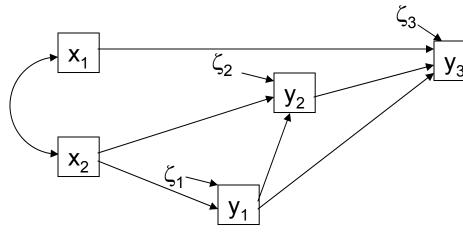
Statistics for Psychosocial Research II:
Structural Models

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Course Overview

- (1) Structural Regression/Path Analysis
 - (a) "effect mediation" versus "controlling for"
 - (b) causality

Course Overview: Structural Equation Models with Observed Variables



(McDonald and Clelland, 1984)

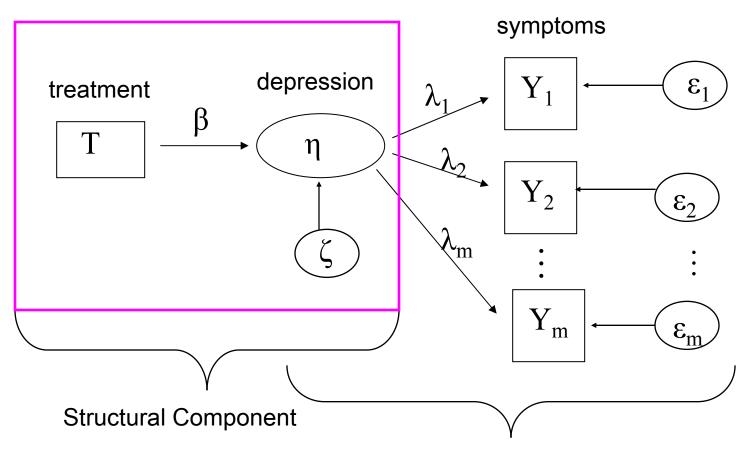
- Study Aim: union sentiment among southern nonunion textile workers
- y_1 deference to managers
- y₂ support for labor activism
- y₃ sentiment toward unions
- x₁ years in textile mill
- x_2 age

Course Overview: Structural Equation Models with <u>Latent</u> Variables

- (2) Regression plus measurement structures from last term
 - (a) if we ignore measurement, "item regression"
 - (b) factor analysis: structural equations with latent variables
 - (c) latent class analysis: latent class regression

Course Overview:

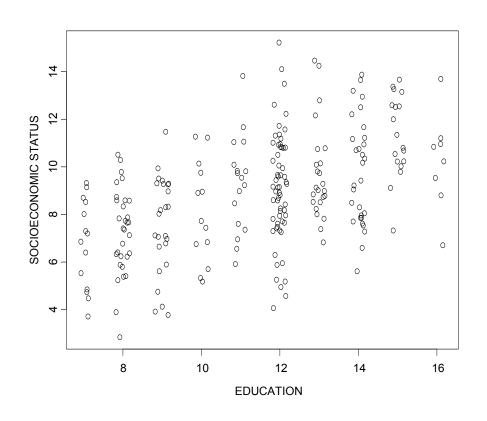
Structural Equations = Structural + Measurement Components



Measurement Component (1st Term)

General Idea

- How does outcome vary with predictors?
- Make inference on hypothesis about how predictors affect outcome
- Predict individual outcomes



Challenge

- How do we measure latent outcomes (and predictors)?
- There are multiple responses
- Approach 1:
 - Y₁,...,Y_n measure the same thing. Treat individually or summarize Y's.
- Approach 2:
 - Call ideal outcome η
 - If we knew η , then $\eta_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + ...$
 - But we don't know it:
 - infer η from factor analysis or latent class analysis
 - ❖ regress η on X's

Three approaches to assessing association between covariates and multiple responses

- (1) Summarize Then Analyze (STA)
- (2) Analyze Then Summarize (ATS)
- (3) Summarize AND Analyze: (SAA)
 - Structural Equations
 - 2 parts
 - measurement component
 - structural/regression component

Example: Depression Study Summarize then Analyze (STA)

- Clinical trial of two antidepressants
- Which anti-depressant is more effective for treating depression?
- Depression symptoms were based on the Hamilton Depression Rating Scale (HAM-D).

17 Symptoms

Depressed mood

Guilt feelings

suicide

Insomnia (x3)

Work and activities

Psychomotor retardation

agitation

anxiety

Somatic symptoms

.

For each item, write the correct number on the line next to the item. (Only one response per item) 1. DEPRESSED MOOD (Sadness, hopeless, helpless, worthless) 0= Absent 1= These feeling states indicated only on questioning 2= These feeling states spontaneously reported 3= Communicates feeling states non-verbally—i.e., through facial expression, posture, voice, and tendency to weep 4= Patient reports VIRTUALLY ONLY these feeling states in his spontaneous verbal and non-verbal communication 2. FEELINGS OF GUILT 0= Absent 1= Self reproach, feels he has let people down 2= Ideas of guilt or rumination over past errors or sinful deeds 3= Present illness is a punishment. Delusions of guilt 4= Hears accusatory or denunciatory voices and/or experiences threatening visual hallucinations 3. SUICIDE 0= Absent 1= Feels life is not worth living 2= Wishes he were dead or any thoughts of possible death to self 3= Suicidal ideas or gesture 4= Attempts at suicide (any serious attempt rates 4) 4. INSOMNIA EARLY 0= No difficulty falling asleep 1= Complains of occasional difficulty falling asleep—i.e., more than ½ hour 2= Complains of nightly difficulty falling asleep 5. INSOMNIA MIDDLE 0= No difficulty 1= patient complains of being restless and disturbed during the night 2= Waking during the night—any getting out of bed rates 2 (except for purposes of voiding) 6. INSOMNIA LATE 0= No difficulty

1= Waking in early hours of the morning but goes back to sleep

2= Unable to fall asleep again if he gets out of bed

Example: Summarize then Analyze (STA)

Summarize:

- Add up the number of symptoms, or "score" the HAM-D.
- Treat the score as "fixed" or "observed" outcome.
- But, we know better! It is not measured perfectly.
- What is the reliability of the HAM-D???
- Analyze: See how the outcome relates to predictor (i.e., treatment)

Summarize Then Analyze

Sum up HAM-D score pre and post and take difference:

Pre-treatment score: $Y_{i1} = Y_{i1,1} + Y_{i1,2} + \cdots + Y_{i1,21}$

Post-treatment score: $Y_{i2} = Y_{i2,1} + Y_{i2,2} + \cdots + Y_{i2,21}$

Difference: $D_i = Y_{i2} - Y_{i1}$

Evaluate association with Y_i and treatment

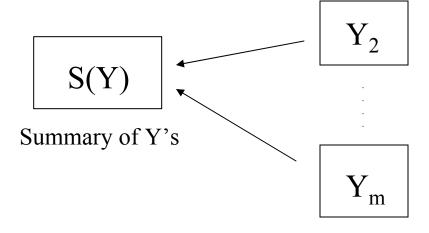
$$D_i = \beta_0 + \beta_1 tr t_i$$

where trt_i = 1 of treatment A, and 0 if treatment B

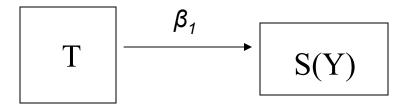
Make inference about treatment effect based on β_1

STA: Two models estimated separately

Model 1:



Model 2:



"treatment"

STA: so what is the problem???

- We are ignoring that S(Y) is measured with error.
- Note that that S(Y) has reliability less than 1.
- In our example: S(Y) represents an "imperfect measure" of depression with reliability of about 0.88 (depending on population).
- Aren't we then overestimating the variation in our outcome by using S(Y)?
- Recall: Var(T_x) < Var(X), T_x is the true score of x
- What effect might that have on the standard error of β_1 ?

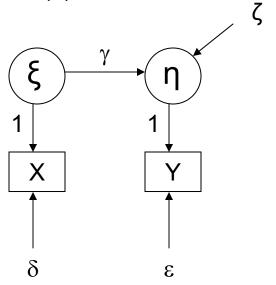
True Model:

$$x = \xi + \delta$$

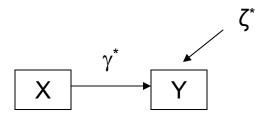
$$y = \eta + \varepsilon$$

$$\eta = \gamma \xi + \zeta$$

(a) True Model



(b) Estimated Model



Bollen, 1989: p155

True Model:
$$x = \xi + \delta$$

 $y = \eta + \varepsilon$
 $\eta = \gamma \xi + \zeta$
 $\cot(\xi, \eta) = \cot(\xi, \gamma \xi + \zeta) = \gamma \phi$
 $\cot(x, y) = \cot(\xi + \delta, \eta + \varepsilon) = \gamma \phi$
 $\gamma^* = \frac{\cot(x, y)}{\cot(x)} = \gamma \left[\frac{\phi}{\cot(x)}\right] = \gamma \rho_{xx}$

 ρ_{xx} = reliability coefficient

Therefore, $|\gamma^*| < |\gamma|$

Note: γ Is not affected by ρ_{vv} !

True Model:
$$x=\xi+\delta$$

$$y=\eta+\varepsilon$$

$$\eta=\gamma\xi+\zeta$$

Also, it can be shown that

$$\rho_{xy}^2 = \rho_{xx} \rho_{yy} \rho_{\xi\eta}^2 \quad \blacksquare$$

$$\rho_{\xi\eta} = \frac{\rho_{xy}}{\sqrt{\rho_{xx}\rho_{yy}}}$$

correction for attenuation of correlation coefficient

i.e. the squared correlation between the two observed measures is attenuated relative to the latent variables whenever the reliability of x or y is less than 1!

In the case of <u>multiple regression</u>, the following is no longer true $| \gamma^* | < | \gamma |$

However, the following still holds:

$$R^2 \geq R^{*2}$$
,

where R² and R^{*2} are the squared mulitple correlation coefficients for the regressions containing variables without and with measurement error, respectively.

Another Approach: Analyze Then Summarize (ATS)

<u>Analyze</u>: for each of the 21 items in the HAM-D, see if treatment is associated with improvement.

1. Define outcome per item:

$$D_{i,1} = Y_{i2,1} - Y_{i1,1}$$

•

$$D_{i,21} = Y_{i2,21} - Y_{i1,21}$$

2. Estimate association per item with treatment:

$$D_{i,1} = \beta_{0,1} + \beta_{1,1} trt_i$$

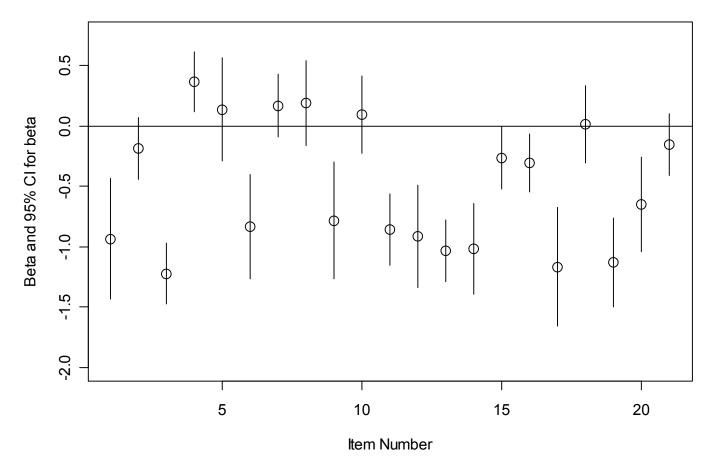
$$D_{i,2} = \beta_{0,2} + \beta_{1,2} trt_i$$

•

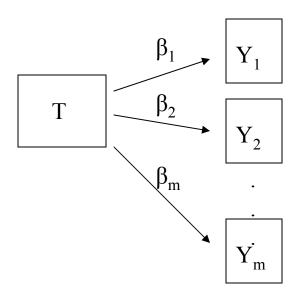
$$D_{i,21} = \beta_{0,21} + \beta_{1,21} trt_i$$

Another Approach: Analyze Then Summarize (ATS)

2. <u>Summarize</u>: Qualitatively or quantitatively evaluate the associations



Analyze then Summarize



Fit *m* regressions to individually describe association between T and each Y.

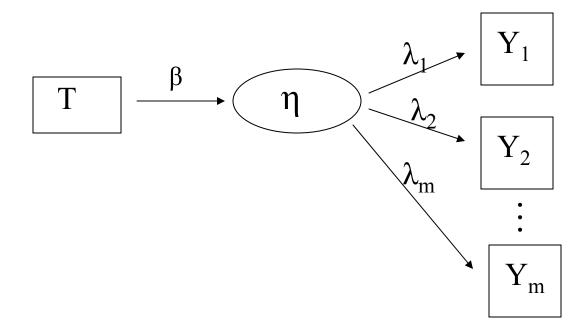
Then summarize associations.

So what is wrong with ATS?

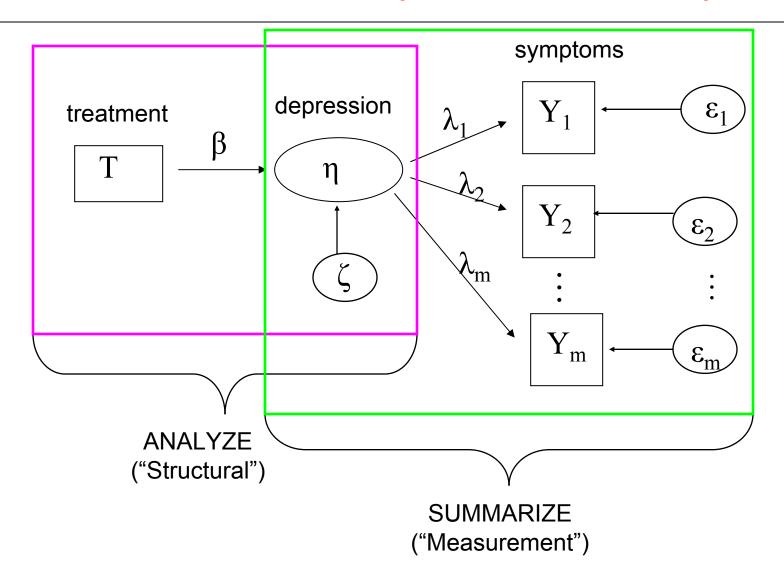
- How do we answer the question: "Which treatment works better?"
- We get individual answers.
- Often hard to summarize after the analysis has been done.
- (More about this in 'Item Regression lecture')

Summarize and Analyze Simultaneously (SAA)

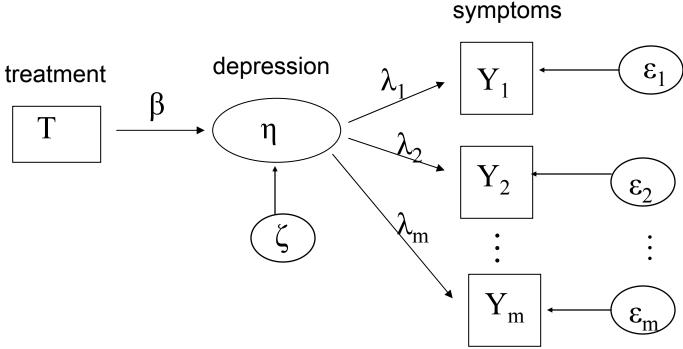
- Fit 'summarize' and 'analyze' components at the same time.
- One big model
- Accounts for measurement error via latent variable



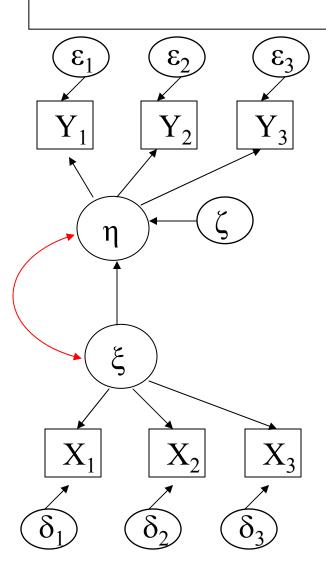
Summarize and Analyze Simultaneously



Summarize and Analyze Simultaneously



Path Notation



Relationships

- straight arrow (causal)
- curved arrow (unspecified)

Variables

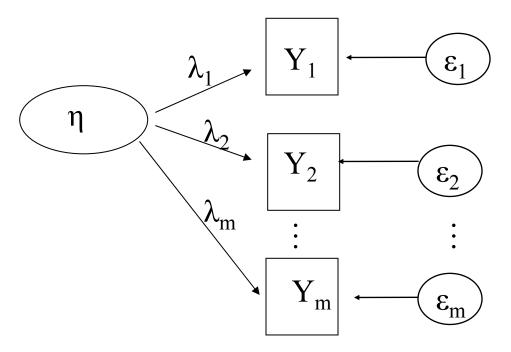
- circles vs. squares
- exogenous (independent)
- endogenous (dependent)

Errors

- one for every endogenous variable
- unexplained component of predicted variables

Components of Structural Equation Model

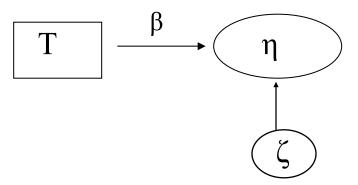
- (A) Measurement Piece
 - how latent variable related to "surrogates"
 - comprised of η's and Y's



Components of Structural Equation Model

(B) Structural Piece

- how latent variable is related to its predictors
- regression
- comprised of η's and T

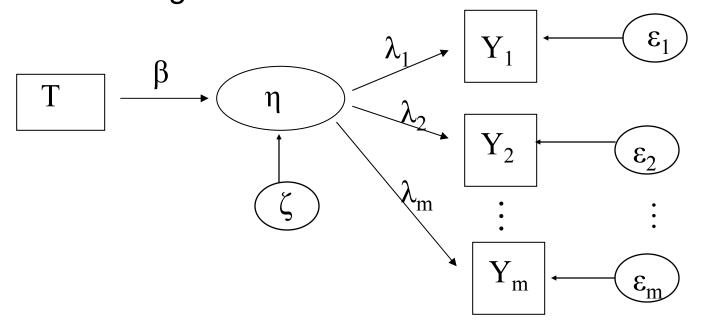


Components of Structural Equation Model

(C) Both components are fit in ONE step

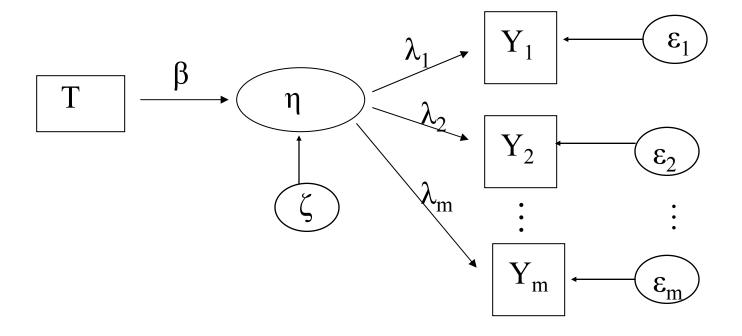
Why better? Does not assume η (i.e., "summary" of Y's) known, which acknowledges measurement error.

Why bad? If model is misspecified, then inference is misleading.



Statistical way of considering relationship between T and Y

$$P(Y = y \mid T) = \sum_{r=1}^{R} P(Y = y, \eta = r \mid T)$$
$$= \sum_{r=1}^{R} P(Y = y \mid \eta = r, T) P(\eta = r \mid T)$$



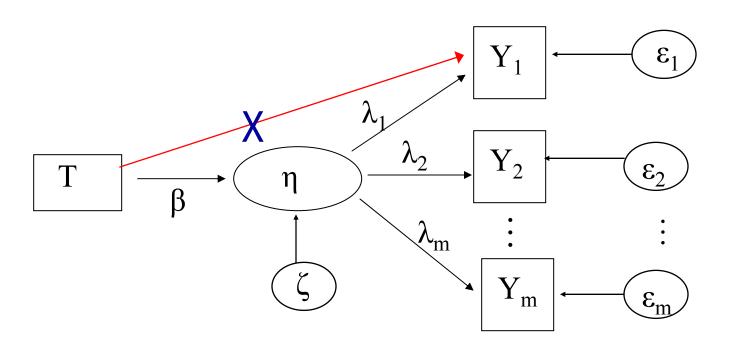
Assumption 1: Non-Differential Measurement

Equivalent interpretations:

- covariates do not predict observed responses after controlling for latent status
- no arrows between T and Y's
- Y and T independent given η

$$P(Y = y | \eta, T) = P(Y = y | \eta)$$

NOT OK UNDER NON-DIFFERENTIAL MEASUREMENT:



Assumption 2: Local/Conditional Independence

Equivalent Interpretations

- latent variable explains all association between observed variables
- no arrows among measurement errors
- observed variables are independent given
 η

$$P(Y_1 = y_1, Y_2 = y_2 \mid \eta) = P(Y_1 = y_1 \mid \eta)P(Y_2 = y_2 \mid \eta)$$

NOT OK UNDER CONDITIONAL INDEPENDENCE:

