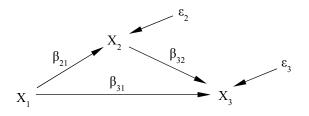
LECTURE 2: DECOMPOSING EFFECTS IN RECURSIVE MODELS

- I. A TWO-EQUATION MODEL IN UNSTANDARDIZED FORM.
- II. AN OVERIDENTIFIED MODEL IN UNSTANDARDIZED FORM
- III. ESTIMATION AND TESTING IN AN UNSTANDARDIZED MODEL
- IV. INTERPRETING STRUCTURAL PARAMETERS IN A THREE-EQUATION MODEL.

I. A TWO-EQUATION MODEL IN UNSTANDARDIZED FORM.



 $X_1 =$ Father's Income,

- $X_2 = Education, and$
- $X_3 = Offspring's Income$

The structural equations are:

$$\begin{split} X_2 &= \beta_{21} \; X_1 + \epsilon_2 \\ X_3 &= \beta_{31} \; X_1 + \beta_{32} \; X_2 + \epsilon_3 \end{split}$$

with six parameters: σ_{11} , β_{21} , β_{31} , β_{32} , $\sigma_{\epsilon 2}$, $\sigma_{\epsilon 3}$. We make the following assumptions:

- 1. $E(X_1\varepsilon_2) = E(X_1\varepsilon_3) = E(X_2\varepsilon_3) = 0$: Disturbances are uncorrelated with regressors.
- 2. $\varepsilon_{2i} \sim N(0, \sigma_{\varepsilon^2})$ and $\varepsilon_{3i} \sim N(0, \sigma_{\varepsilon^3})$: Disturbances are normally-distributed with constant variance.
- 3. $E(\varepsilon_{2i}, \varepsilon_{2j}) = E(\varepsilon_{3i}, \varepsilon_{3j}) = 0$: Disturbances are not serially correlated.
- 4. $E(\varepsilon_2 \varepsilon_3) = 0$: The two disturbances are uncorrelated.

Again, we characterize the three random variables in terms of observable moments:

$$\begin{array}{c} \Sigma = \\ 3 \times 3 \end{array} \begin{bmatrix} \sigma_{11} \\ \sigma_{21} \\ \sigma_{31} \\ \sigma_{32} \\ \sigma_{33} \end{bmatrix}$$

Now let's express our moments in terms of parameters:

$$\begin{array}{l} X_2 = \beta_{21} \; X_1 + \epsilon_2 \\ X_3 = \beta_{31} \; X_1 + \beta_{32} \; X_2 + \epsilon_3 \end{array}$$

1.
$$\sigma_{11} = E(X_1^2) = \sigma_{11}$$

 $\sigma_{21} = E(X_1X_2) = E[X_1(\beta_{21}X_1 + \epsilon_2)] = \beta_{21}E(X_1^2) + E(X_1\epsilon_2)$

2. $\sigma_{21} = \beta_{21} \sigma_{11}$

$$\sigma_{31} = E(X_1X_3) = E[X_1(\beta_{31}X_1 + \beta_{32}X_2 + \varepsilon_3)] = \beta_{31}E(X_1^2) + \beta_{32}E(X_1X_2) + E(X_1\varepsilon_3) = \beta_{31}\sigma_{11} + \beta_{32}\sigma_{21}$$

3. $\sigma_{31} = \beta_{31} \sigma_{11} + \beta_{32} \sigma_{21}$ (almost - substitute for σ_{21} and get $\sigma_{31} = \beta_{31} \sigma_{11} + \beta_{32} \beta_{21} \sigma_{11}$)

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 $\begin{aligned} \sigma_{32} &= E(X_2X_3) = E[X_2(\beta_{31} X_1 + \beta_{32}X_2 + \epsilon_3)] = \beta_{31}E(X_1X_2) + \beta_{32}E(X_2X_2) + E(X_2\epsilon_3) = \beta_{31} \sigma_{21} + \beta_{32}\sigma_{22} \\ \textbf{4.} \quad \sigma_{32} &= \beta_{31} \sigma_{21} + \beta_{32}\sigma_{22} \quad [almost - \sigma_{32} = \beta_{31} \beta_{21} \sigma_{11} + \beta_{32} (\beta_{21}^2\sigma_{11} + \sigma_{\epsilon22})] \\ \sigma_{22} &= E(X_2^{-2}) = E[(\beta_{21}X_1 + \epsilon_2)(\beta_{21}X_1 + \epsilon_2)] = \beta_{21}^{-2}E(X_1^{-2}) + 2\beta_{21}E(X_1\epsilon_2) + E(\epsilon_2\epsilon_2) \\ \textbf{5.} \quad \sigma_{22} &= \beta_{21}^2\sigma_{11} + \sigma_{\epsilon22} \\ \sigma_{33} &= E(X_3^{-2}) = E[(\beta_{31}X_1 + \beta_{32}X_2 + \epsilon_3)(\beta_{31}X_1 + \beta_{32}X_2 + \epsilon_3)] = \beta_{31}^{-2}E(X_1^{-2}) + 2\beta_{31}\beta_{32}E(X_2X_1) + 2\beta_{31}E(X_1\epsilon_3) + \beta_{32}^{-2}E(X_2^{-2}) + 2\beta_{32}E(X_2\epsilon_3) + E(\epsilon_3\epsilon_3) \\ \sigma_{33} &= \beta_{31}^{-2}\sigma_{11} + 2\beta_{31}\beta_{32}\sigma_{21} + \beta_{32}^{-2}\sigma_{22} + \sigma_{\epsilon33} \end{aligned}$

But a more useful result for σ_{33} results from multiplying the X_3 equation by X_3 :

$$E(X_3 X_3) = \beta_{31} E(X_3 X_1) + \beta_{32} E(X_3 X_2) + E(X_3 \varepsilon_3)$$

 $= \beta_{31} \sigma_{31} + \beta_{32} \sigma_{32} + E(X_3 \varepsilon_3) \qquad \text{But, multiply the } X_3 \text{ equation by } \varepsilon_3 \text{: } E(X_3 \varepsilon_3) = \beta_{31} E(X_1 \varepsilon_3) + \beta_{32} E(X_2 \varepsilon_3) + E(\varepsilon_3^2) = \sigma_{\varepsilon_3 3}$

6.
$$\sigma_{33} = \beta_{31} \sigma_{31} + \beta_{32} \sigma_{32} + \sigma_{\epsilon 33}$$

Now we can rearrange these equations into a population moment (covariance) matrix implied by the population structural equation model. This gives moments almost in terms of parameters. Again, if the model is correct, this matrix should generate the observed covariance matrix.

$$\begin{bmatrix} \sigma_{11} & & \\ \sigma_{21} & \sigma_{22} & \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix} = \begin{bmatrix} \sigma_{11} & & & & \\ \beta_{21} \sigma_{11} & & & & & \\ \beta_{31} \sigma_{11} + \beta_{32} \sigma_{21} & & & & \\ \beta_{31} \sigma_{11} + \beta_{32} \sigma_{21} & & & & \\ \beta_{31} \sigma_{21} + \beta_{32} \sigma_{22} & & & \\ \beta_{31} \sigma_{31} + \beta_{32} \sigma_{32} + \sigma_{\epsilon_{33}} \end{bmatrix}$$

Let's express parameters in terms of moments:

1.
$$\sigma_{11} = \sigma_{11}$$

2.
$$\beta_{21} = \sigma_{21}/\sigma_{11}$$

For β_{31} , begin with (3)

 $\sigma_{31} = \beta_{31} \sigma_{11} + (\beta_{32}) \sigma_{21} \qquad \text{from (4) } \sigma_{32} = \beta_{31} \sigma_{21} + \beta_{32} \sigma_{22}; \text{ so } \beta_{32} = (\sigma_{32} - \beta_{31} \sigma_{21})/\sigma_{22}$ $\sigma_{31} = \beta_{31} \sigma_{11} + \sigma_{21}(\sigma_{32} - \beta_{31} \sigma_{21})/\sigma_{22} \qquad \text{substitute for } \beta_{32}$ $\sigma_{31} - \beta_{31} \sigma_{11} = (\sigma_{21} \sigma_{32} - \beta_{31} \sigma_{21}^{2})/\sigma_{22} \qquad \text{subtract } \beta_{31} \sigma_{11} \text{ from both sides}$ $\sigma_{22} \sigma_{31} - \beta_{31} \sigma_{22} \sigma_{11} = \sigma_{21} \sigma_{32} - \beta_{31} \sigma_{21}^{2} \qquad \text{multiply both sides by } \sigma_{22}$ $\sigma_{22} \sigma_{31} - \sigma_{21} \sigma_{32} = \beta_{31} \sigma_{22} \sigma_{11} - \beta_{31} \sigma_{21}^{2} \qquad \text{add } \beta_{31} \sigma_{22} \sigma_{11} \text{ to both sides}; \qquad \text{subtract } \sigma_{32} \text{ from both sides}$

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 $σ_{22} σ_{31} - σ_{21} σ_{32} = β_{31} (σ_{22} σ_{11} - σ_{21}^{2})$ factor out $β_{31}$ from right side

3. $\beta_{31} = (\sigma_{22} \sigma_{31} - \sigma_{21} \sigma_{32})/(\sigma_{11} \sigma_{22} - \sigma_{21}^2)$ divide both sides by $(\sigma_{22} \sigma_{11} - \sigma_{21}^2)$

4.
$$\beta_{32} = (\sigma_{11} \sigma_{32} - \sigma_{21} \sigma_{31})/(\sigma_{11} \sigma_{22} - \sigma_{21}^2)$$
 Same as above, but using (4) for (3) and (3) for (4)

For the disturbances,

 $\sigma_{22} = \beta_{21}^{2} \sigma_{11} + \sigma_{\epsilon 22} \qquad \text{from (5)}$ $\sigma_{\epsilon 22} = \sigma_{22} - \beta_{21}^{2} \sigma_{11} = \sigma_{22} - (\sigma_{21}^{2} / \sigma_{11}^{2}) \sigma_{11}$ **5.** $\sigma_{\epsilon 22} = \sigma_{22} - (\sigma_{21}^{2} / \sigma_{11})$ $\sigma_{33} = \beta_{31} \sigma_{31} + \beta_{32} \sigma_{32} + \sigma_{\epsilon 33} \qquad \text{from (6)}$

6. $\sigma_{\epsilon 33} = \sigma_{33} - \beta_{31} \sigma_{31} - \beta_{32} \sigma_{32}$

We can compute the reduced-form by replacing X_2 in our second structural equation with the right-hand side of our first equation.

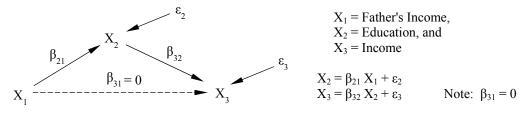
$$X_2 = \beta_{21} X_1 + \epsilon_2 = \pi_{21} X_1 + \pi_{\epsilon_2}$$
 Only exogenous variables in structural form, so reduced form = structural form

$$X_{3} = \beta_{31} X_{1} + \beta_{32} (X_{2}) + \varepsilon_{3}$$

= $\beta_{31} X_{1} + \beta_{32} (\beta_{21} X_{1} + \varepsilon_{2}) + \varepsilon_{3}$
= $\beta_{31} X_{1} + \beta_{32} \beta_{21} X_{1} + \beta_{32} \varepsilon_{2} + \varepsilon_{3}$
= $(\beta_{31} + \beta_{32} \beta_{21}) X_{1} + \beta_{32} \varepsilon_{2} + \varepsilon_{3}$
 $X_{3} = \pi_{31} X_{1} + \pi_{\varepsilon_{3}}$ where $\pi_{31} = \beta_{31} + \beta_{32} \beta_{21}$
 $\pi_{\varepsilon_{3}} = \beta_{32} \varepsilon_{2} + \varepsilon_{3}$

II. AN OVERIDENTIFIED MODEL IN UNSTANDARDIZED FORM

Now consider Model II in unstandardized form:



We can obtain expressions for moments in terms of parameters by simply constraining $\beta_{31} = 0$ in the above normal equations:

1. $\sigma_{11} = \sigma_{11}$ 4. $\sigma_{21} = \beta_{21} \sigma_{11}$

2. $\sigma_{22} = \beta_{21}^2 \sigma_{11} + \sigma_{\epsilon 22}$ 5. $\sigma_{31} = \beta_{32} \sigma_{21}$

3.
$$\sigma_{32} = \beta_{32} \sigma_{22}$$
 6. $\sigma_{33} = \beta_{32}^2 \sigma_{22} + \sigma_{\epsilon 33}$ or $\sigma_{33} = \beta_{32} \sigma_{32} + \sigma_{\epsilon 33}$ (from constraining Model I)

Or in our covariance structure matrix form:

$$\begin{bmatrix} \sigma_{11} & & \\ \sigma_{21} & \sigma_{22} & \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix} = \begin{bmatrix} \sigma_{11} & & & & & \\ \beta_{21} \sigma_{11} & & & & & \beta_{21}^2 \sigma_{11} + \sigma_{\epsilon_{22}} \\ \beta_{32} \sigma_{21} & & & & & & \beta_{32}^2 \sigma_{22} + \sigma_{\epsilon_{33}} \end{bmatrix}$$

$$\sum_{\substack{\Sigma \\ 3 \times 3}} \sum_{\substack{3 \times 3}} \sum_{\substack{\Sigma(\theta) = \\ 3 \times 3}} \sum_{\substack{3 \times 3}} \sum_{\substack{\Sigma(\theta) = \\ 3 \times 3}$$

From these normal equations, we can express parameters in terms of moments (again, notice there is one more equation than parameter, since we eliminated β_{31} .

1.
$$\sigma_{11} = \sigma_{11}$$

2. $\beta_{21} = \sigma_{21}/\sigma_{11}$
3. $\beta_{32} = \sigma_{31}/\sigma_{21} = \sigma_{32}/\sigma_{22}$ from (3) and (5)

 $\sigma_{\epsilon 22} = \sigma_{22} - (\beta_{21}^2 \sigma_{11}) = \sigma_{22} - (\sigma_{21}^2 \sigma_{11}^2 \sigma_{11}) = \sigma_{22} - \sigma_{21}^2 \sigma_{11}$

4.
$$\sigma_{\epsilon 22} = \sigma_{22} - \sigma_{21}^2 / \sigma_{11}$$

$$\sigma_{\epsilon_{33}} = \sigma_{33} - \beta_{32}^2 \sigma_{22} = \sigma_{33} - (\sigma_{31}^2 / \sigma_{21}^2) \sigma_{22} = \sigma_{33} - (\sigma_{32}^2 / \sigma_{22}^2) \sigma_{22} \quad \text{(because of two ways of computing } \beta_{32})$$

5. $\sigma_{\epsilon_{33}} = \sigma_{33} - (\sigma_{31}^2 / \sigma_{21}^2) \sigma_{22} = \sigma_{33} - (\sigma_{32}^2 / \sigma_{22})$

Note that this model implies one overidentifying restriction, which resulted from our assumption that $\beta_{31} = 0$ in the population. We can compute it from either (3) or (5) by setting the two equivalent ways of computing β_{32} or $\sigma_{\epsilon 33}$ to be equal, and cross-multiplying: $\sigma_{31}/\sigma_{21} = \sigma_{32}/\sigma_{22}$; therefore,

$\sigma_{31} \sigma_{22} = \sigma_{32} \sigma_{21}$

If the model is true in the population this constraint on the observable moments (covariances) will hold exactly. If it doesn't hold exactly, the model is wrong. Stated differently, if $\beta_{31} \neq 0$, then the model is wrong, and our overidentifying constraint on moments will not hold. Note the parallel with our standardized model.

III. ESTIMATION AND TESTING IN AN UNSTANDARDIZED MODEL

Since we rarely have access to population moments, we must typically rely on sample moments to estimate structural parameters.

$$\begin{split} \mathbf{S} &= \begin{bmatrix} \mathbf{S}_{11} & & \\ \mathbf{S}_{21} & \mathbf{S}_{22} & \\ \mathbf{S}_{31} & \mathbf{S}_{32} & \mathbf{S}_{33} \end{bmatrix} \\ & \boldsymbol{\Sigma}(\hat{\theta}) &= \begin{bmatrix} \mathbf{S}_{11} & & \\ \hat{\beta}_{21} \, \mathbf{S}_{11} & & & \hat{\beta}_{21}^2 \, \mathbf{S}_{11} + \, \mathbf{S}_{\epsilon 22} \\ & \hat{\beta}_{32} \, \mathbf{S}_{21} & & & & \hat{\beta}_{32} \, \mathbf{S}_{22} + \, \mathbf{S}_{\epsilon 33} \end{bmatrix} \end{split}$$

- 1. $s_{11} = s_{11}$
- 2. $\hat{\beta}_{21} = s_{21}/s_{11}$
- 3. $\hat{\beta}_{32} = s_{31}/s_{21} = s_{32}/s_{22}$
- 4. $s_{\epsilon 22} = s_{22} s_{21}^2/s_{11} = s_{33} (s_{32}^2/s_{22})$
- 5. $s_{\epsilon 33} = s_{33} (s_{31}^2/s_{21}^2) s_{22} = s_{33} (s_{32}^2/s_{22})$

And the overidentifying restriction on sample moments is: $s_{31} s_{22} = s_{32} s_{21}$. As in the standardized case, there are two ways of estimating β_{32} . Which method do we use? Again, we could use s_{31}/s_{21} or s_{32}/s_{22} , since both are unbiased $E(s_{31}/s_{21}) = E(s_{32}/s_{22}) = \beta_{32}$. Or we could use some weighted average of the two $w_1(s_{31}/s_{21}) + w_2(s_{32}/s_{22})$, which will also be unbiased $E[w_1(s_{31}/s_{21}) + w_2(s_{32}/s_{22})] = \beta_{32}$. All three will be unbiased, but one will be the most efficient. Theorems of ordinary least squares estimation tells us that $\hat{\beta}_{32} = s_{32}/s_{22}$ is efficient (minimum variance):

$$\operatorname{VAR}(\hat{\beta}_{32}) \leq \operatorname{VAR}(\hat{\beta}_{32}^{*})$$
, where $\hat{\beta}_{32}^{*}$ is any other linear unbiased estimator of β_{32} and $\operatorname{VAR}(\hat{\beta}_{32}) = \operatorname{E}[\hat{\beta}_{32} - \operatorname{E}(\hat{\beta}_{32})]^2$ and $\operatorname{VAR}(\hat{\beta}_{32}^{*}) = \operatorname{E}[\hat{\beta}_{32}^{*} - \operatorname{E}(\hat{\beta}_{32}^{*})]^2$

Aside: the reason is that VAR($\hat{\beta}_{32}$) is equivalent to the Cramer-Rao lower bound, which is the lower bound of the variance of an unbiased estimator under mild regularity conditions, see Theil (1971) or Greene (2003). Thus, to get an efficient estimator in this case use weights $w_1 = 0$ and $w_2 = 1.0$. Again, this weighting scheme only yields efficient estimators in recursive models in observables (and the assumptions of linearity, model specification, and disturbance specification hold). In general, we will have to use a different weighting scheme to get efficient estimators.

Now, how do we test Model I versus Model II? We could try to develop a confidence interval or hypothesis test of the above restriction on sample moments. But a better way would be to test the parameters that differentiate Model I and Model II directly, since theoretically given our structural model, they are what we're interested in. Let's go back to Model I (the less-restrictive model) and replace population moments with sample moments to arrive at an estimator.

$$\begin{bmatrix} s_{11} \\ s_{21} \\ s_{31} \\ s_{32} \\ s_{31} \end{bmatrix} = \begin{bmatrix} s_{11} \\ \hat{\beta}_{21} \\ s_{11} \\ \hat{\beta}_{31} \\ s_{11} + \beta_{32} \\ s_{21} \end{bmatrix} = \begin{bmatrix} s_{11} \\ \hat{\beta}_{21} \\ s_{11} + s_{\epsilon 22} \\ \hat{\beta}_{31} \\ s_{21} + \hat{\beta}_{32} \\ s_{22} \\ \hat{\beta}_{31} \\ s_{31} + \hat{\beta}_{32} \\ s_{32} + s_{\epsilon 33} \end{bmatrix}$$

1. $s_{11} = s_{11}$

- 2. $\hat{\beta}_{21} = s_{11}/s_{21}$
- 3. $\hat{\beta}_{31} = (s_{22} s_{31} s_{21} s_{32})/(s_{11} s_{22} s_{21}^2)$
- 4. $\hat{\beta}_{32} = (s_{11} s_{32} s_{21} s_{31})/(s_{11} s_{22} s_{21}^2)$
- 5. $s_{\epsilon 33}^* = s_{33} \hat{\beta}_{31} s_{31} \hat{\beta}_{32} s_{32}$

Again, since this is a recursive model in observables, these are OLS estimators which are unbiased and efficient. To form confidence intervals and perform hypothesis tests, we need to calculate the standard errors of the estimates. First, since we assumed that $\epsilon_{331} \sim N(0, \sigma_{\epsilon 33})$, we can assume that $\wedge_{31} \sim N(\beta_{31}, \sigma_{\beta 31}^2)$.

Second, we need an unbiased estimator of the variance disturbance $\sigma_{\epsilon_{33}}$. The estimator, $s_{\epsilon_{33}}^*$, of equation (5) gives a biased estimate of $\sigma_{\epsilon_{33}}$, because it doesn't take into consideration the number of parameters we have estimated in the equation for X_3 . Theorems of least squares residuals tell us that an unbiased estimator of $\sigma_{\epsilon_{33}}$ is:

$$s_{\epsilon 33} = (N - 1)/(N - 2) (s_{33} - \hat{\beta}_{31} s_{31} - \hat{\beta}_{32} s_{32})$$

This is the two-variable case of the more general result for K parameters (variables) in the X_3 equation:

$$\mathbf{s}_{\varepsilon_{33}} = (N-1)/(N-K) \left(\mathbf{s}_{33} - \hat{\beta}_{31} \, \mathbf{s}_{31} - \hat{\beta}_{32} \, \mathbf{s}_{32} - \dots - \, \hat{\beta}_{3K} \, \mathbf{s}_{3K} \right)$$

And the adjusted $R^2 = 1 - s_{\varepsilon 33}/s_{33}$

Aside: Note that this is the usual least squares residual estimator (Kmenta *Elements of Econometrics* 1971, p. 361):

 $s_{\epsilon_{33}} = 1/(N - K) (m_{33} - \hat{\beta}_{31} m_{31} - \hat{\beta}_{32} m_{32} - ... - \hat{\beta}_{3K} m_{3K})$, where $m_{ij} = (N - 1) s_{ij}$ are sums of squares and cross-products.

We can obtain the variances of our estimators (Kmenta 1971):

$$\sigma_{\beta 31}^{2} = (\sigma_{\epsilon 33} s_{22})/(s_{11} s_{22} - s_{21}^{2})$$

$$\sigma_{\beta 32}^{2} = (\sigma_{\epsilon 33} s_{11})/(s_{11} s_{22} - s_{21}^{2})$$

But we usually don't know the value of $\sigma_{\epsilon 33}$, so we use our unbiased estimator above. The standard error of the estimate is the square root of this:

$$\begin{split} s_{\beta 31} &= \left[(s_{\epsilon 33} \ s_{22}) / (s_{11} \ s_{22} - s_{21}^2) \right]^{\frac{1}{2}} \\ s_{\beta 32} &= \left[(s_{\epsilon 33} \ s_{11}) / (s_{11} \ s_{22} - s_{21}^2) \right]^{\frac{1}{2}} \end{split}$$

We can then form t-statistics:

$$t_{\beta 31,n-2} = (\hat{\beta}_{31} - \beta_0)/s_{\beta 31}$$
$$t_{\beta 32,n-2} = (\hat{\beta}_{32} - \beta_0)/s_{\beta 32}$$

and perform tests of hypotheses. For example, we can test Model II against Model I by testing H_0 : $\beta_{31} = 0$ versus H_1 : $\beta_{31} \neq 0$:

Model II $H_0: \beta_{31} = 0$ (Null Hypothesis) Model I $H_1: \beta_{31} \neq 0$ (Alternative Hypothesis)

 $t_{\beta 31,n-2} = \hat{\beta}_{31}/s_{\beta 31}$

(Aside: Note that we are not testing Model I here—it is the maintained alternative hypothesis.)

Or, as we learned from our regression class, we can use an F-test to test the joint hypothesis: $\beta_{31} = \beta_{32} = 0$. In general, the following is true:

 $[SSR/(K-1)]/[SSE/(N-K)] \sim F_{K-1, N-K} \text{ where } SSE = S_{\epsilon 33}(N-K), \text{ } SST = s_{33}(N-1), \text{ and because } SST = SSR + SSE, \text{ it follows that } SSR = SST - SSE$

In this case, $[SSR/(2-1)]/[SSE/(N-2)] \sim F_{1, N-2}$

The important point here is that for estimation and testing in recursive models in observables, we can rely completely on the general linear regression model estimated by ordinary least squares. For multiple equation models, simply use equation-by-equation ordinary least squares regressions, and use conventional t-tests and F-tests to test hypotheses. In the above example, we would run two regressions: regressing X_2 on X_1 , and regressing X_3 on X_1 and X_2 . To get the reduced form for the second equation, we could regress X_3 on the exogenous variable(s), X_1 . We can accomplish this using the regression algorithm in any statistical software package, such as Regression in SPSS or Stata. Given the output, we can decompose total effects into direct and indirect components, compute standardized coefficients, and test hypotheses about specific parameters.

Aside: For those interested in the generalization of these results to the multiparameter single-equation case in matrix algebra, we can related our results to the general linear model. For the general case, the standard errors of the K-explanatory variables can be obtained by taking the square roots of the diagonal elements of the estimated covariance matrix of the estimator (see Kmenta 1971, pp. 357-64):

$COV(\hat{\theta}) =$	$\sigma^{2} (X'X)^{-1}$	where $\hat{\theta} = [\hat{\theta}_1, \hat{\theta}_2,, \hat{\theta}_k]'$ is a k x 1 vector of coefficients, and σ^2 is the
$\mathbf{k} \times \mathbf{k}$	$\mathbf{k} \times \mathbf{k}$	variance of the disturbance, and X'X ⁻¹ is the inverse of the sums of squares and
		cross-products of X.

We usually don't know σ^2 , so we estimate it using the least squares residual estimator s², which gives us the estimated covariance matrix of the estimator: s² (X'X)⁻¹

We can translate this into our notation as follows. Let $\sigma^2 = \sigma_{\epsilon 33}$, and $s^2 = s_{\epsilon 33}$. Then let S_x be the k x k submatrix of S representing the covariance matrix of Xs (predictors) only. Therefore, $S_x = (1/N - 1) X'X$, and $S_x^{-1} = (N-1) (X'X)^{-1}$

 $COV(\hat{\theta}) = \sigma_{\epsilon 33} / (N-1) S_x^{-1} k \times k k \times k$

Then, since $s^2 = s_{\epsilon 33}$, our estimated covariance matrix of $\hat{\theta}$ is: $s_{\epsilon 33}(N - 1) S_x^{-1}$, and the standard errors are the square roots of the diagonal elements of the k x k matrix.

To test overidentifying restrictions on two nested recursive models, use the following F-test:

$$F = \frac{[ESS(R) - ESS(U)]/r}{ESS(U)/(N - K - 1)}$$

with r and N- K - 1 degrees of freedom, where ESS(R) is the error sums of squares from the restricted model ($\beta = \beta_0$, β is an r x 1 vector of restricted coefficients) and ESS(U) is the error sums of squares for the unrestricted model $\beta \neq \beta_0$, and r is the number of restrictions.

LISREL EXAMPLE:

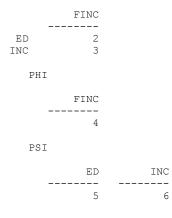
Let's estimate our model using the following hypothetical data:

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FINC ED INC [1.0] $\Sigma_{\rho} =$.48 1.0 3×3 L.50 .45 1.0 SD' = .40 2.9 .41 LISREL gives us a path diagram: The following lines were read from file -6.47 ED H:\529 examples\2-eq model.LS8: TWO EQUATION PATH MODEL 0.16-FINC DA NI=3 NO=578 ñ. SD * 2.9 .41 .40 INC -0.12 КM * 1.0 .48 1.0 1.0 .50 .45 LA Chi-Square=0.00, df=0, P-value=1.00000, RMSEA=0.000 FINC ED INC SE 2 3 1/ MO NX=1 NY=2 GA=FU, FR BE=FU, FI PS=DI, FR FR BE 2 1 VA 0.3 GA 1 1 PD OU ME=ML SC TWO EQUATION PATH MODEL Number of Input Variables 3 Number of Y - Variables 2 Number of X - Variables 1 Number of ETA - Variables 2 Number of KSI - Variables 1 Number of Observations 578 TWO EQUATION PATH MODEL Covariance Matrix ΕD INC FINC _____ _____ _____ ΕD 8.41 0.17 INC 0.54 FINC 0.56 0.08 0.16 TWO EQUATION PATH MODEL Parameter Specifications BETA ΕD INC ____ ____ 0 0 ΕD INC 1 0 GAMMA

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Covariance Structure Analysis (LISREL) Lecture Notes



TWO EQUATION PATH MODEL

Number of Iterations = 4

LISREL Estimates (Maximum Likelihood)

	ED	INC
ΕD		
INC	0.04	
	(0.01)	
	6.90	

GAMMA

	FINC
ΕD	3.48
	(0.27)
	13.13
INC	0.38
	(0.04)
	9.34

Covariance Matrix of Y and X

	ED	INC	FINC
ΕD	8.41		
INC	0.54	0.17	
FINC	0.56	0.08	0.16

PHI

FINC
0.16
(0.01)
16.97

PSI Note: This matrix is diagonal.

ED	INC

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Covariance Structure Analysis (LISREL) Lecture Notes

6.470.12(0.38)(0.01)16.9716.97

Squared Multiple Correlations for Structural Equations

ED INC 0.23 0.31

Squared Multiple Correlations for Reduced Form

ED	INC
0.23	0.25

Reduced Form

	FINC
ΕD	3.48
	(0.27)
	13.13
INC	0.51
	(0.04)
	13.86

Goodness of Fit Statistics

Degrees of Freedom = 0 Minimum Fit Function Chi-Square = 0.00 (P = 1.00) Normal Theory Weighted Least Squares Chi-Square = 0.00 (P = 1.00)

The Model is Saturated, the Fit is Perfect !

TWO EQUATION PATH MODEL

Standardized Solution

BETA

	ED	INC
ED.		
ЕD		
INC	0.27	
GAM	AN	

	FINC	
ΕD	0.48	
INC	0.37	

Correlation Matrix of Y and X

	ED	INC	FINC
ED	1.00		
INC	0.45	1.00	
FINC	0.48	0.50	1.00
PSI Note:	This matri	x is diag	onal.

ED INC

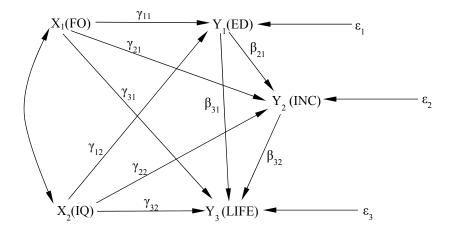
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0.77 0.69 Regression Matrix Y on X (Standardized) FINC ED 0.48 INC 0.50 Time used: 0.031 Seconds

IV. INTERPRETING STRUCTURAL PARAMETERS IN A THREE-EQUATION MODEL.

Let's decompose total (reduced-form) effects into direct and indirect effects using path analysis, which was developed by the population geneticist, Sewall Wright. In this exercise, we are in the population (we are God), and don't have to worry about sample data, estimation, statistical inference or testing). We just compute the population parameters.

Consider the following model:



I've changed notation slightly, using gamma, γ , as a parameter relating exogenous variables (Xs) to endogenous variables (Ys), while reserving betas, β s, as parameters relating endogenous variables to other endogenous variables.

$$\begin{split} Y_1 &= \gamma_{11} X_1 + \gamma_{12} X_2 + \epsilon_1 \\ Y_2 &= \gamma_{21} X_1 + \gamma_{22} X_2 + \beta_{21} Y_1 + \epsilon_2 \\ Y_3 &= \gamma_{31} X_1 + \gamma_{32} X_2 + \beta_{31} Y_1 + \beta_{32} Y_2 + \epsilon_3 \end{split}$$

Again, assume we're in deviation scores, and that we've made the usual assumptions about the disturbances, plus the following additional assumptions:

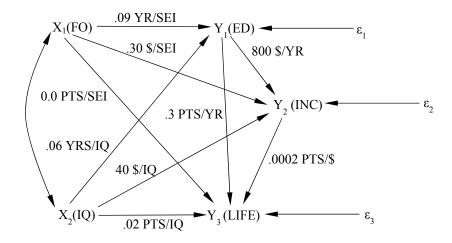
 $E(\varepsilon_1 \varepsilon_2) = E(\varepsilon_1 \varepsilon_3) = E(\varepsilon_2 \varepsilon_3) = 0$ $E(X_1 \varepsilon_1) = E(X_1 \varepsilon_2) = E(X_1 \varepsilon_3) = E(X_2 \varepsilon_1) = E(X_2 \varepsilon_2) = E(X_2 \varepsilon_3) = 0$ $E(Y_1 \varepsilon_2) = E(Y_1 \varepsilon_3) = E(Y_2 \varepsilon_3) = 0$

We begin with the population (covariances) moments among observables:

$$\begin{split} \Sigma &= \begin{bmatrix} X_1 & X_2 & Y_1 & Y_2 & Y_3 \\ 400 & & & \\ 150 & 225 & & \\ 45 & 27 & 9 & \\ 54 & 29 & 9.6 & 36 & \\ 27.6 & 19.8 & 5.2 & 10.9 & 9 \end{bmatrix} \qquad \sigma = \begin{bmatrix} 20 \ SEI \\ 15 \ IQ \\ 3 \ YRS \\ \$6K \\ 3PTS \end{bmatrix} \end{split}$$

Note: square roots of diagonal elements of Σ gives a vector of standard deviations:

If we computed parameters in terms of moments, we'd come up with the following values for structural parameters:



Our three equations (in their structural form) look as follows (standardized parameters appear in parentheses):

$$\begin{array}{rcl} Y_1 &=& .09 \ X_1 + .06 \ X_2 + \epsilon_1 \\ && (.60) && (.30) \\ Y_2 &=& 30 \ X_1 + 40 \ X_2 + 800 \ Y_1 + \epsilon_2 \\ && (.10) && (.10) && (.40) \\ Y_3 &=& 0.0 \ X_1 + .02 \ X_2 + .30 \ Y_1 + .0002 \ Y_2 + \epsilon_3 \\ && (.00) && (.10) && (.30) && (.40) \end{array}$$

What do these parameter values of direct effects tell us about stratification and quality of life? Note that if we were working with sample data, we could use multiple regression to obtain OLS estimates of the parameters of our three equations. But we can also decompose total effects into direct and indirect effects, which would tell us more about the specific mechanisms operating here. Recall that to get total effects we compute reduced forms from the above structural forms. The structural form of the Y_1 equation is also the reduced form (since it doesn't contain any endogenous predictors). Let's begin with Y_2 equation:

 $Y_2 = \gamma_{21} X_1 + \gamma_{22} X_2 + \beta_{21} \frac{Y_1}{Y_1} + \varepsilon_2$

Replace Y_1 with the structural equation for $Y_1 = \frac{\gamma_{11} X_1 + \gamma_{12} X_2 + \varepsilon_1}{\gamma_{11} X_1 + \gamma_{12} X_2 + \varepsilon_1}$.

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$$Y_{2} = \gamma_{21} X_{1} + \gamma_{22} X_{2} + \beta_{21} (\gamma_{11} X_{1} + \gamma_{12} X_{2} + \epsilon_{1}) + \epsilon_{2}$$
Substitute for Y_{1}

$$= \gamma_{21} X_{1} + \gamma_{22} X_{2} + \gamma_{11} \beta_{21} X_{1} + \gamma_{12} \beta_{21} X_{2} + \beta_{21} \epsilon_{1} + \epsilon_{2}$$
Multiply terms

$$= \gamma_{21} X_{1} + \gamma_{11} \beta_{21} X_{1} + \gamma_{22} X_{2} + \gamma_{12} \beta_{21} X_{2} + \beta_{21} \epsilon_{1} + \epsilon_{2}$$
Rearrange terms

$$= (\gamma_{21} + \gamma_{11} \beta_{21}) X_{1} + (\gamma_{22} + \gamma_{12} \beta_{21}) X_{2} + (\beta_{21} \epsilon_{1} + \epsilon_{2})$$
Factor terms by X_{1} and X_{2}

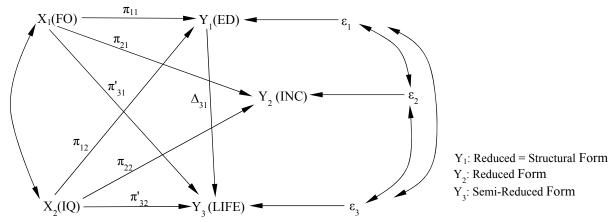
$$Y_{2} = \pi_{21} X_{1} + \pi_{22} X_{2} + \pi_{22} X_{2} + \pi_{22}$$

Aside: If we were working with sample data and had to estimate the reduced-form parameters, π s, we could simply regress Y_2 on X_1 and X_2 using OLS to get unbiased and efficient estimates, since $E(\pi_{\epsilon 2} X_1) = E(\pi_{\epsilon 2} X_2) = 0$.

If you look closely at the π s, notice that they contain a direct effect of X plus indirect effects of X (products of parameters) through intervening variables. In general, reduced-form coefficients give total effects, which can be decomposed into direct and indirect effects. In our example,

For the effect of	X_1 (FO) on Y_2 (INC)	For the effect of X_2 (IQ) on Y_2 (INC)	
π_{21} =	$\gamma_{21} + \gamma_{11} \beta_{21}$	$\pi_{22} \qquad = \qquad \gamma_{22} + \gamma_{12} \beta_{21}$	
Total Effect = (of FO on INC)	Direct + Indirect Effect (FO through El		
102 \$/SEI = (.34)	30\$ / SEI + 72 \$/SEI (.30) (.04)	$\begin{array}{rcl} 88 \ \$/IQ & = & 40 \ \$/IQ & + & 48 \ \$/IQ \\ (.22) & & (.10) & & (.12) \end{array}$	2

What does this tell us substantively?



Here is a path diagram of the reduced form of Y_1 and Y_2 , and the semi-reduced form for Y_3 :

We can do the same for our equation for quality of life, Y_3 . But here we have two endogenous variables, Y_1 and Y_2 . We can do two substitutions. The first, substituting Y_2 with its equation gives us the semi-reduced form:

$$Y_{3} = \gamma_{31} X_{1} + \gamma_{32} X_{2} + \beta_{31} Y_{1} + \beta_{32} Y_{2} + \varepsilon_{3}$$

= $\gamma_{31} X_{1} + \gamma_{32} X_{2} + \beta_{31} Y_{1} + \beta_{32} (\gamma_{21} X_{1} + \gamma_{22} X_{2} + \beta_{21} Y_{1} + \varepsilon_{2}) + \varepsilon_{3}$
= $(\gamma_{31} + \gamma_{21} \beta_{32}) X_{1} + (\gamma_{32} + \gamma_{22} \beta_{32}) X_{2} + (\beta_{31} + \beta_{21} \beta_{32}) Y_{1} + (\beta_{32} \varepsilon_{2} + \varepsilon_{3})$

 $Y_3 = \pi'_{31} X_1 + \pi'_{32} X_2 + \Delta_{31} Y_1 + \pi'_{\varepsilon_3}$

where π ' means semi-reduced form and Δ refers to the total effect of an endogenous variable. For our example, we again can compute direct effects of our predictors, and the indirect effects through schooling:

For the effect of X_1 (FO) on Y_3 (LIFE) For the effect of X_2 (IQ) on Y_3 (LIFE) π'_{31} $= \gamma_{31} + \gamma_{21}$ π'_{32} β32 $= \gamma_{32} + \gamma_{22}$ β_{32} Semi-Total Effect = Direct + Indirect Effect Semi-Total Effect = Direct + Indirect Effect (of FO on LIFE) Effect (FO through INC) (of IQ on LIFE) Effect (IQ thru INC) .006 PTS/SEI = 0 PTS/SEI + .006 PTS/SEI .028 PTS/IQ = .02 PTS/IQ + .008 PTS/IQ(.04) (0.0)(.04)(.10) (.14) (.04)

For the effect of Y_1 (ED) on Y_3 (LIFE)

 $\Delta_{31} = \beta_{31} + \beta_{21}\beta_{32}$ Total Effect = Direct + Indirect Effect (of ED on LIFE) Effect (ED through INC)

.46 PTS/YR = .30 PTS/YR + .16 PTS/YR(.46) (.30) (.16)

Again, what does this tell us substantively? Finally, we can compute the reduced-form of our Y_3 equation. We can start with our semi-reduced form equation (which already substituted for Y_2) and substitute for Y_1 .

 $Y_{3} = (\gamma_{31} + \gamma_{21} \beta_{32}) X_{1} + (\gamma_{32} + \gamma_{22} \beta_{32}) X_{2} + (\beta_{31} + \beta_{21} \beta_{32}) Y_{1} + (\beta_{32} \epsilon_{2} + \epsilon_{3})$

Now substitute for $Y_1 = \gamma_{11} X_1 + \gamma_{12} X_2 + \varepsilon_1$

$$Y_{3} = (\gamma_{31} + \gamma_{21} \beta_{32}) X_{1} + (\gamma_{32} + \gamma_{22} \beta_{32}) X_{2} + (\beta_{31} + \beta_{21} \beta_{32}) (\gamma_{11} X_{1} + \gamma_{12} X_{2} + \epsilon_{1}) + (\beta_{32} \epsilon_{2} + \epsilon_{3})$$

If we multiply this out, which is very tedious, we arrive at:

$$Y_{3} = (\gamma_{31} + \gamma_{21} \beta_{32}) X_{1} + (\gamma_{32} + \gamma_{22} \beta_{32}) X_{2} + \gamma_{11} \beta_{31} X_{1} + \gamma_{12} \beta_{31} X_{2} + \beta_{31} \epsilon_{1} + \gamma_{11} \beta_{21} \beta_{32} X_{1} + \beta_{31} \epsilon_{1} + \gamma_{11} \beta_{31} \delta_{1} + \beta_{31} \delta_{1} \delta_{1} + \beta_{31} \delta_{1} \delta_{1} + \beta_{31} \delta_{1} \delta_{1} \delta_{1} + \beta_{31} \delta_{1} \delta_{$$

$$\gamma_{12} \beta_{31} \beta_{32} X_2 + \beta_{21} \beta_{32} \epsilon_1 + (\beta_{32} \epsilon_2 + \epsilon_3)$$

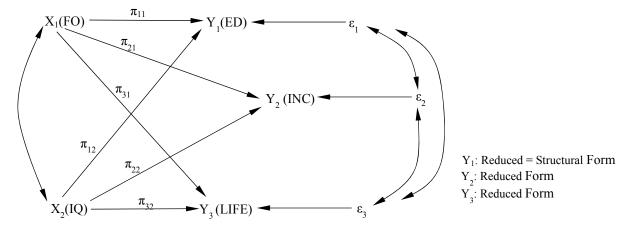
$$Y_{3} = \underbrace{(\gamma_{31} + \gamma_{11} \beta_{31} + \gamma_{21} \beta_{32} + \gamma_{11} \beta_{21} \beta_{32})}_{\pi_{31} X_{1}} X_{1} + \underbrace{(\gamma_{32} + \gamma_{12} \beta_{31} + \gamma_{22} \beta_{32} + \gamma_{12} \beta_{31} \beta_{32})}_{\pi_{32} X_{2}} X_{2} + \underbrace{(\beta_{21} \beta_{32} \epsilon_{1} + \beta_{32} \epsilon_{2} + \epsilon_{3})}_{+\pi_{\epsilon 3}}$$

For the effect of
$$X_1$$
 (FO) on Y_3 (LIFE) For the effect of X_2 (IQ) on Y_3 (LIFE)

 $\pi_{31} = \gamma_{31} + \gamma_{11} \beta_{31} + \gamma_{21} \beta_{32} + \gamma_{11} \beta_{21} \beta_{32} \qquad \pi_{32} = \gamma_{32} + \gamma_{12} \beta_{31} + \gamma_{22} \beta_{32} + \gamma_{12} \beta_{21} \beta_{32}$

Total EffectDirect+ Indirect EffectsTotal Effect= Direct+ Indirect Effects(of FO on LIFE)Effect(through ED & INC)(of IQ on LIFE)Effect(through ED & INC).048 PTS/SEI0.0 PTS/SEI+ .048 PTS/SEI.056 PTS/IQ= .02 PTS/IQ + .036 PTS/IQ(.32)(0.0)(.32)(.28)(.10)(.18)

Give a substantive interpretation to these direct and indirect effects. Here is a path diagram of the model in its reduced form for all equations:



We can place these parameter values in a table:

		Pred	letermine	d Variable	es		
Equation	Dependent Variable	X ₁ FO	X ₂ IQ	Y ₁ ED	Y ₂ INC	σ_{ϵ}	R^2
1.	Y ₁ ED	.09 (.60)	.06 (.30)			1.82	.63
2.	Y ₂ INC	102 (.34)	88 (.22)			5235	.24
3.	Y ₂ INC	30 (.10)	40 (.10)	800 (.40)		5057	.30
4.	Y ₃ LIFE	.048 (.32)	.056 (.28)			2.56	.27
5.	Y ₃ LIFE	.006 (.04)	.028 (.14)	.46 (.46)		2.41	.35
6.	Y ₃ LIFE	.000 (.00)	.020 (.10)	.30 (.30)	.0002 (.40)	2.20	.46

Note: Standardized coefficients appear in parentheses.

In this table, the single equation (line 1) for education is both structural and reduced forms. The equation for income appears in reduced-form in line 2 and structural form in line 3. The equation for quality of life appears in reduced-form in line 2, semi-reduced form in line 5, and structural form in line 6. As an exercise, study the relationships between this table, the path diagram, and the above equations.

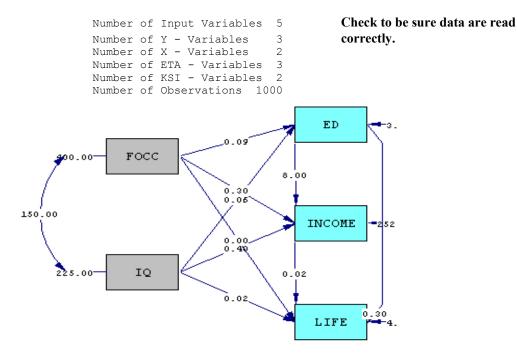
Here is the model run in LISREL 8.8, with the output annotated:

1. First the full model:

The following lines were read from file C:\529 examples\status2.ls8: STATUS ATTAINMENT AND LIFE SATISFACTION (DA)ta line NI means number of input observable DA NI=5 NO=1000 variables. NO is number of observations. SD I'm inputting standard deviations (SD) and a correlation matrix (KM) 20 15 3 60.00 3 ΚM 1.00 .500 1.00 .750 .600 1.00 .450 .390 .535 1.00 .460 .440 .580 .605 1.00 LA stands for labels; * means free format LA * Here I'm (SE)lecting variables to analyze; y's first, x's FOCC IQ ED INCOME LIFE next. The backslash says stop here. SE 34512\ (MO)del parameters. NX is # Xs; NY is # Ys. BE is MO NX=2 NY=3 GA=FU, FR BE=FU, FI PS=DI, FR full & fixed; PS is diagonal and free. I then free select FR BE 3 2 BE 3 1 BE 2 1 Bs. (OU)put. PD asks for a path diagram. РD OU ME=ML RS EF SC Method of estimation is (M)aximum (L)ikelihood. RS asks for (R)esiduals and *fitted* moment matrix $\Sigma(\hat{\theta})$. EF asks for total and indirect effects, SC for completely standardized

solution.

STATUS ATTAINMENT AND LIFE SATISFACTION



STATUS	ATTAINMENT	AND	LIFE	SATISFACTION
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Covariance Matrix = S

	ED	INCOME	LIFE	FOCC	IQ
ED	9.00				
INCOME	96.30	3600.00			
LIFE	5.22	108.90	9.00		
FOCC	45.00	540.00	27.60	400.00	
IQ	27.00	351.00	19.80	150.00	225.00

STATUS ATTAINMENT AND LIFE SATISFACTION

```
Parameter Specifications Note: 0 means the matrix elements is a constant (fixed). Parameters to be estimated (free) are numbered.
```

BETA = Matrix of regression coefficients among endogenous variables (etas – η) (here ys)

	ED	INCOME	LIFE			
				0	0	0
ED	0	0	0	β ₂₁	0	$0 = \mathbf{B}$
INCOME	1	0	0	β ₃₁	β ₃₂	0
LIFE	2	3	0	• • •		

GAMMA = Matrix of coefficients from regressing etas (η) on ksis (ξ) – or in this case x on y

	FOCC	IQ	γ11	γ12	γ13
			Y21	γ ₂₁	$\gamma_{23} = \Gamma$
ED	4	5	Y 31	Y23	Y33
INCOME	6	7	•		•
LIFE	8	9			

Covariance matrix among exogenous variables (ksis ξ); E($\xi \xi$ ') = Φ

	FOCC	IQ	Φ11		=Φ
			φ ₂₁	φ ₁₁	
FOCC	10			•	
IQ	11	12			

Covariance matrix of disturbances (psi ζ); E($\zeta \zeta$ ') = Ψ

ED	INCOME	LIFE	Ψ11			
			0	Ψ22		= Ψ
13	14	15	0	0	Ψ33	

STATUS ATTAINMENT AND LIFE SATISFACTION

=

=

Number of Iterations = 0

PHI

PSI

LISREL Estimates (Maximum Likelihood)

Note: Matrix entries are unstandardized estimates, standard errors (in parentheses) and t-values. Also recall that ML in fully-recursive linear models in observables is exactly equation-by-equation OLS.

BETA	Ą		
	ED	INCOME	LIFE
ED			
INCOME	8.00 (0.87) 9.17		
LIFE	0.30 (0.04) 7.65	0.02 (0.00) 14.57	
GAMI	AN		
ED	FOCC 0.09 (0.00) 26.97	IQ 0.06 (0.00) 13.49	
INCOME	0.30 (0.12) 2.48	0.40 (0.13) 3.00	
LIFE	0.00 (0.01) 0.02	0.02 (0.01) 3.43	
Cova	ariance M	atrix of Y	and X
	ED	INCOME	LIFE
ED INCOME	9.00 96.30	3600.00	

ED	9.00				
INCOME	96.30	3600.00			
LIFE	5.22	108.90	9.00		
FOCC	45.00	540.00	27.60	400.00	
IQ	27.00	351.00	19.80	150.00	225.00

PHI

	FOCC	IQ
FOCC	400.00	
	(17.92)	
	22.33	
IQ	150.00	225.00
	(10.62)	(10.08)
	14.12	22.33

PSI

Note: This matrix is diagonal.

ED	INCOME	LIFE
3.33	2527.20	4.82
(0.15)	(113.19)	(0.22)
22.33	22.33	22.33

Squared Multiple Correlations for Structural Equations ${\ensuremath{R}}\xspace$

FOCC

IQ

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These are Pi's in our notation π_{yx}

ED	INCOME	LIFE
0.63	0.30	0.46

NOTE: Rý for Structural Equations are Hayduk's (2006) Blocked-Error Rý

Reduced Form

	FOCC	IQ
ED	0.09 (0.00) 26.97	0.06 (0.00) 13.49
INCOME	1.02 (0.10) 10.66	0.88 (0.13) 6.90
LIFE	0.05 (0.00) 10.24	0.06 (0.01) 8.96

Squared Multiple Correlations for Reduced Form (Note the magnitudes compared to the structural form.)

LIFE	INCOME	ED
0.27	0.24	0.63

Goodness of Fit Statistics

Degrees of Freedom = 0 Minimum Fit Function Chi-Square = 0.0 (P = 1.00) Normal Theory Weighted Least Squares Chi-Square = 0.00 (P = 1.00)

The Model is Saturated, the Fit is Perfect !

STATUS ATTAINMENT AND LIFE SATISFACTION

Standardized Solution

BETA

e.g., $\beta \sigma_x / \sigma_y = P_{yx}^{\beta}$	LIFE	INCOME	ED	
$c.g., po_x, o_y = y_x$				ED
		0.40	0.40 0.30	INCOME LIFE

GAMMA

e.g., $\gamma \sigma_x / \sigma_y = P_{yx}^{\gamma}$

	FOCC	IQ
ΕD	0.60	0.30
INCOME	0.10	0.10
LIFE	0.00	0.10

Correlation Matrix of Y and X e.g., ρ_{xy}

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	ED	INCOME	LIFE	FOCC	IQ	
ED INCOME LIFE FOCC IQ	1.00 0.53 0.58 0.75 0.60	1.00 0.60 0.45 0.39	1.00 0.46 0.44	1.00 0.50	1.00	
PS	SI ote: This mat	rix is dia	gonal.			
	ED	INCOME	LIFE			
	0.37	0.70	0.54			
Re	egression Mat	rix Y on X	(Standardi:	zed)		
	FOCC	IQ		_	_	
			e.	g., $\pi_{yx} \sigma_x /$	$\sigma_{y} = P_{yx}^{\pi}$	
ED INCOME LIFE	0.34	0.30 0.22 0.28				
STATUS ATT	TAINMENT AND	LIFE SATIS	FACTION			
Total and	Indirect Eff	fects				
Τc	otal Effects FOCC	of X on Y IQ	Reduced	Form π's		
ED	0.09	0.06	π_{11} π_{21}			
22		(0.00) 13.49	π_{31}			
INCOME	1.02 (0.10) 10.66	0.88 (0.13) 6.90				
LIFE	0.05 (0.00) 10.24	0.06 (0.01) 8.96				
Ir	ndirect Effec	cts of X on	Y			
	FOCC	IQ				
ED						
INCOME	0.72 (0.08) 8.68	0.48 (0.06) 7.58	$(\gamma_{11}\beta_{21})$		$(\gamma_{12} \beta_{21})$	
LIFE	0.05 (0.00) 11.36	0.04 (0.00) 9.01	$(\gamma_{31}+\gamma_{21}\beta_{32})$	$_{2} + \gamma_{11} \beta_{31} + \gamma_{11}$	$\beta_{21} \beta_{32}$) ($\gamma_{32} + \gamma_2$	$_{22} \beta_{32} + \gamma_{12} \beta_{31} + \gamma_{12} \beta_{21} \beta_{31}$
Tc	otal Effects	of Y on Y				

 β_{32}

	ED	INCOME	LIFE			
ED						
INCOME	8.00 (0.87) 9.17			β ₂₁		
LIFE	0.46 (0.04) 11.08			$\beta_{31}+\beta_{32}\ \beta_{21}$		
Largest	Eigenvalue	of B*B' (Sta	ability Index	k) is 64.092		
Inc	direct Effec	ts of Y on Y	ľ			
	ED	INCOME	LIFE			
ED						
INCOME						
LIFE	0.16 (0.02) 7.76			β_{32} β_{21}		
STATUS ATTAINMENT AND LIFE SATISFACTION						
Standardize	ed Total and	Indirect E:	ffects			
Sta	andardized T	otal Effect:	s of X on Y			

 FOCC
 IQ

 ED
 0.60
 0.30

 INCOME
 0.34
 0.22

 LIFE
 0.32
 0.28

Standardized Indirect Effects of X on Y

	FOCC	IQ
ED		
INCOME	0.24	0.12
LIFE	0.32	0.18

Standardized Total Effects of Y on Y

	ED	INCOME	LIFE
ED			
INCOME	0.40		
LIFE	0.46	0.40	

Standardized Indirect Effects of Y on Y

	ED	INCOME	LIFE
ED			
INCOME			

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LIFE 0.16 -- --

Time used: 0.031 Seconds

2. Now let's run a constrained model, in which we constrain $\gamma_{31} = \gamma_{21} = 0$:

The following lines were read from file C:\529 examples\status6.ls8:

```
STATUS ATTAINMENT AND LIFE SATISFACTION GA31=GA32=0
DA NI=5 NO=1000
SD
*
20 15 3 60.00 3
ΚM
1.00
.500 1.00
.750 .600 1.00
.450 .390 .535 1.00
.460 .440 .580 .605 1.00
LA
*
FOCC IQ ED INCOME LIFE
SE
34512\
MO NX=2 NY=3 GA=FU,FR BE=FU,FI PS=DI,FR
FR BE 3 2 BE 3 1 BE 2 1
FI GA 3 1 GA 3 2
                             Here I'm fixing GA 3 1 and GA 3 2 so they're not estimated
VA 0 GA 3 1 GA 3 2
                             I'm giving the fixed parameters values of zero
PD
OU ME=ML RS EF SC
                                                              ED
                                                                       -3.33
                                                0.09
                                 FOCC
                      400.00
                                                        8.00
                                               0.30
                                               0.05
                 150.00
                                                            INCOME
                                                                       2527.20
                                               0.40
                      225.00
                                  IQ
                                                        0.02
                                                                     0.35
                                                             LIFE
                                                                        4.88
```

Chi-Square=11.74, df=2, P-value=0.00282, RMSEA=0.070

STATUS ATTAINMENT AND LIFE SATISFACTION GA31=GA32=0 $\ensuremath{\mathsf{GA31}}$

Number of Input Variables5Number of Y - Variables3Number of X - Variables2Number of ETA - Variables3Number of KSI - Variables2Number of Observations1000

STATUS ATTAINMENT AND LIFE SATISFACTION GA31=GA32=0

Covariance Matrix

	ED	INCOME	LIFE	FOCC	IQ
ED	9.00				
INCOME	96.30	3600.00			
LIFE	5.22	108.90	9.00		
FOCC	45.00	540.00	27.60	400.00	
IQ	27.00	351.00	19.80	150.00	225.00

Parameter Specifications

BETA			
	ED	INCOME	LIFE
-			
ED INCOME	0 1	0 0	0 0
LIFE	2	3	0
GAMM			
	FOCC	IQ	
-			
ED	4	5	
INCOME	6 0	7 0	
LIFE	0	0	
PHI			
	FOCC	IQ	
-			
FOCC	8		
IQ	9	10	
PSI			
101	ED	INCOME	LIFE
-			
	11	12	13

Number of Iterations = 12

LISREL Estimates (Maximum Likelihood)

BETA

	ED	INCOME	LIFE
ED			
INCOME	8.00 (0.87) 9.17		
LIFE	0.36 (0.03) 13.01	0.02 (0.00) 14.96	

Note effects of FOCC and IQ are fixed.

G	AMMA					
	FOCC	IQ				
ED	0.09 (0.00)	0.06 (0.00) 13.49				
INCOME		0.40 (0.13) 3.00				
LIFE				`Note: No	estimate for GA	A 31 and GA 3 2
С	ovariance M	atrix of Y a	and X			
	ED		LIFE	FOCC		
ED INCOME LIFE FOCC IQ	9.00 96.30 5.22 45.00	3600.00	9.00 27.31			
Ρ		IQ				
FOCC	400.00 (17.92) 22.33					
IQ		225.00 (10.08) 22.33				
	SI					
IN		atrix is dia INCOME	-			
	3.33 (0.15)	2527.20 (113.19) 22.33	4.88 (0.22)			
S	quared Mult	iple Correla	ations for S	tructural E	Iquations	
	ED	INCOME				
	0.63	0.30	0.46			
NOTE: RÝ	for Structu	ral Equatior	ns are Haydu	ık's (2006)	Blocked-Error	Rý
R	educed Form					
	FOCC	IQ				
ED	0.09 (0.00) 26.97	0.06 (0.00) 13.49				
INCOME	1.02 (0.10) 10.66	0.88 (0.13) 6.90				
LIFE	0.05 (0.00)	0.04 (0.00)				

16.04 10.65 Squared Multiple Correlations for Reduced Form INCOME ED LIFE _____ _____ _____ 0.24 0.63 0.24 Goodness of Fit Statistics Degrees of Freedom = 2Minimum Fit Function Chi-Square = 11.81 (P = 0.0027) 2df test of γ 31 γ 32 = 0 Normal Theory Weighted Least Squares Chi-Square = 11.74 (P = 0.0028) Estimated Non-centrality Parameter (NCP) = 9.74 90 Percent Confidence Interval for NCP = (2.45 ; 24.50) Minimum Fit Function Value = 0.012 Population Discrepancy Function Value (F0) = 0.009890 Percent Confidence Interval for F0 = (0.0025 ; 0.025) Root Mean Square Error of Approximation (RMSEA) = 0.070 90 Percent Confidence Interval for RMSEA = (0.035; 0.11) P-Value for Test of Close Fit (RMSEA < 0.05) = 0.16Expected Cross-Validation Index (ECVI) = 0.038 90 Percent Confidence Interval for ECVI = (0.031 ; 0.053) ECVI for Saturated Model = 0.030ECVI for Independence Model = 2.94 Chi-Square for Independence Model with 10 Degrees of Freedom = 2918.03 Independence AIC = 2928.03 Model AIC = 37.74Saturated AIC = 30.00Independence CAIC = 2957.57Model CAIC = 114.54Saturated CAIC = 118.62Normed Fit Index (NFI) = 1.00 Non-Normed Fit Index (NNFI) = 0.98 Parsimony Normed Fit Index (PNFI) = 0.20 Comparative Fit Index (CFI) = 1.00Incremental Fit Index (IFI) = 1.00 Relative Fit Index (RFI) = 0.98 Critical N (CN) = 784.72Root Mean Square Residual (RMR) = 0.74 Standardized RMR = 0.016Goodness of Fit Index (GFI) = 1.00 Adjusted Goodness of Fit Index (AGFI) = 0.96 Parsimony Goodness of Fit Index (PGFI) = 0.13 STATUS ATTAINMENT AND LIFE SATISFACTION GA31=GA32=0 Fitted Covariance Matrix $=\sum (\hat{\theta})$ INCOME LIFE FOCC ED IQ _____ _____ _____ ΕD 9.00 3600.00 INCOME 96.30
 108.90
 9.00

 540.00
 27.31

 351.00
 16.94
 LIFE 5.22

351.00

Fitted Residuals = $\sum (\hat{\theta}) - S$

45.00

27.00

FOCC

ТО

400.00 150.00

225.00

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INCOME LIFE FOCC ED IQ _____ _____ _____ _____ _____ ΕD - -- -INCOME 0.00 0.00 0.00 - - 0.29 0.00 2.86 LIFE 0.00 - -FOCC - -IQ - -_ _ Summary Statistics for Fitted Residuals Smallest Fitted Residual = 0.00 Median Fitted Residual = 0.00 Largest Fitted Residual = 2.86 Stemleaf Plot - 0|000000000000 0|3 1| 2|9 Standardized Residuals INCOME LIFE FOCC IQ ED _____ - -ΕD _ _ - -TNCOME - -LIFE - -- -FOCC - -0.32 IQ - -- -3.42 - -- -Summary Statistics for Standardized Residuals 0.00 Smallest Standardized Residual = Median Standardized Residual = Median Standardized Residual = 0.00 Largest Standardized Residual = 3.42 Stemleaf Plot 0|0000000000003 1| 2| 3|4 Largest Positive Standardized Residuals Residual for IQ and LIFE 3.42 STATUS ATTAINMENT AND LIFE SATISFACTION GA31=GA32=0 Standardized Solution BETA ΕD INCOME LIFE -----_____ - -- -- -0.41 ED - -INCOME 0.40 - -_ _ 0.36 LIFE GAMMA FOCC IO _____ _____ ED 0.60 INCOME 0.10 0.30 LIFE - -

Correlation Matrix of Y and X

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	ED	INCOME	LIFE	FOCC	IQ
FOCC	0.75	1.00 0.60 0.45 0.39	0.46	1.00 0.50	1.00
PSI Note	e: This mat	rix is diag	onal.		
	ED	INCOME	LIFE		
-	0.37	0.70	0.54		
Regi	ression Mat	rix Y on X	(Standardiz	ed)	
	FOCC	IQ			
	0.60 0.34 0.36				
STATUS ATTAINMENT AND LIFE SATISFACTION GA31=GA32=0					

Total and Indirect Effects

Total Effects of X on Y

	FOCC	IQ
ED	0.09	0.06
	(0.00)	(0.00)
	26.97	13.49
INCOME	1.02	0.88
	(0.10)	(0.13)
	10.66	6.90
LIFE	0.05	0.04
	(0.00)	(0.00)
	16.04	10.65

Indirect Effects of X on Y

	FOCC	IQ	
ED			
INCOME	0.72 (0.08) 8.68	0.48 (0.06) 7.58	
LIFE	0.05 (0.00) 16.04	0.04 (0.00) 10.65	

Total Effects of Y on Y

	ED	INCOME	LIFE
ED			
INCOME	8.00 (0.87) 9.17		

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Covariance Structure Analysis (LISREL) Lecture Notes

LIFE 0.52 0.02 - -(0.03) (0.00) 17.65 14.96 Largest Eigenvalue of B*B' (Stability Index) is 64.129

Indirect Effects of Y on Y

	ED	INCOME	LIFE
ED			
INCOME			
LIFE	0.17 (0.02) 7.82		

STATUS ATTAINMENT AND LIFE SATISFACTION GA31=GA32=0

Standardized Total and Indirect Effects

Standardized Total Effects of X on Y

	FOCC	IQ
ED	0.60	0.30
INCOME	0.34	0.22
LIFE	0.36	0.20

Standardized Indirect Effects of X on Y

	FOCC	IQ
ED		
INCOME	0.24	0.12
LIFE	0.36	0.20

Standardized Total Effects of Y on Y

	ED	INCOME	LIFE
ED			
INCOME	0.40		
LIFE	0.52	0.41	

Standardized Indirect Effects of Y on Y

	ED	INCOME	LIFE
ED			
INCOME			
LIFE	0.17		

Time used: 0.016 Seconds